NBER WORKING PAPER SERIES

DEBT, INFORMATION, AND ILLIQUIDITY

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Working Paper 25054
http://www.nber.org/papers/w25054

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
September 2018

We thank Yakov Amihud and Bengt Holmstrom for numerous conversations. We also thank Jack Bao, Pierre Collin-Dufresne, Douglas Diamond, Marty Eichanbaum, Paul Gao, Gary Gorton, Joel Hasbrouck, Christopher Hennessy, Charlie Himmelberg, Ryan Israelsen, Ralph Koijen, Arvind Krishnamurthy, Gregor Matvos, Toby Moskowitz, Jun Pan, Dimitris Papanikolaou, Adriano Rampini, Sergio Rebelo, Alexi Savov, Stephen Schaefer, Adi Sunderam, Jeremy Stein, Steve Strongin, S. Viswanathan, Avi Whol, Brian Weller, and seminar participants at AQR, Baruch College, Boston College, Brigham Young University, Catolica Lisbon School of Business and Economics, Duke University, The Federal Reserve Board of Governors, Goldman Sachs Global Markets Institute Academic Fellowship Conference, The Hebrew University in Jerusalem, Kellogg School of Management, London Business School, London School of Economics, Michigan State University, NBER Summer Institute: Macro, Money and Financial Frictions, Notre Dame (Mendoza), NYU Stern, Stanford Conference in Honor of Bengt Holmstrom, Tel Aviv University, University of Amsterdam, University of Miami, University of Texas at Austin, University of Texas Dallas, and University of Washington. We are grateful to Jack Bao and Kewei Hou for sharing their bond liquidity data. Yupeng Wang provided excellent research assistance. We thank the Goldman Sachs Global Markets Institute for financial support. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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NBER Working Paper No. 25054
September 2018
JEL No. E44,E51,G01,G12,G14,G32

ABSTRACT

We analyze the empirical determinants of liquidity in debt markets in light of predictions stemming from debt-based information theories. We conduct a battery of tests confirming predictions of asymmetric information models of bond liquidity, including those that predict a``hockey-stick" relation between bond liquidity and underlying fundamental value. When debt is deep in the money, it becomes informationally insensitive and more liquid. In contrast, when firm value deteriorates towards the left tail, the value of debt becomes informationally sensitive and less liquid. We alleviate endogeneity concerns using exogenous variation in firm value that is plausibly not driven by bond liquidity. Our results shed new empirical light on the determination of liquidity in debt markets.

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Introduction

What determines liquidity in debt markets? Going back to seminal work by Akerlof (1970) and Spence (1973), a large theoretical literature emphasizes the role that information asymmetries play in determining liquidity in asset markets. If information asymmetries regarding asset payoffs are sufficiently severe, adverse selection will inhibit trade between buyers and sellers. Beyond information asymmetries, other theories and frameworks have been proposed in understanding the determinants of liquidity in asset markets. These include limited risk bearing capacity among intermediaries, market maker inventory risk, search-based models, and models of heterogeneous beliefs.[1]

A more recent theoretical literature applies insights from information economics to the question of liquidity in *debt* markets. Prominent examples include Dang et al. (2012, 2013) and Holmström (2015), which analyze how the information sensitivity of debt and the varying nature of this sensitivity affect liquidity and liquidity dry-ups in debt markets. In this paper, we empirically analyze the determinants of liquidity in debt markets in light of these debt-based information theories.

Before describing the empirical analysis, it is useful to review the intuition behind Dang et al. (2012).[2] The main idea is that the well-known "hockey-stick" functional form of debt payoffs is key in understanding debt liquidity.[3] Because of this functional form, when debt is deep in the money – that is, when the distribution of underlying firm value is concentrated in the right tail, where the probability of default is low – debt becomes informationally insensitive. Regardless of the realization of underlying firm value, the market value of debt will be very close to its face value. Thus, even if parties may enjoy an informational advantage regarding underlying *firm* value, when debt is relatively deep in the money, this informational advantage will not translate into asymmetric information regarding *debt* value. Liquidity in this informationally insensitive region is predicted to be high.

Consider, then, what happens when firm value deteriorates toward the left tail, with a distribution that is centered closer to the "kink" of the hockey-stick-shaped payoff (that is, below which the firm defaults on maturity). In this region of payoffs, the value of debt becomes very sensitive to private information since below the default threshold debt payoffs move one for one with firm value. Trading parties therefore have strong incentives to develop and acquire information about underlying debt value. Information asymmetries will be relatively high in this informationally sensitive region. As debt values deteriorate and enter

[1] See, e.g., Stoll (1978), Grossman and Miller (1988), Varian (1989), Harris and Raviv (1993), Brunnermeier and Pedersen (2006), Garleanu and Pedersen (2007), Weill (2007), and He and Milbradt (2014).

[2] Holmström (2015) provides a nontechnical description of Dang et al. (2012).

[3] This shape is, of course, determined by the put option the debtor owns.

the informationally sensitive region, liquidity will thus fall.[4] Liquidity is thus endogenously affected by variation in underlying asset values.[5]

Testing the mechanisms behind asymmetric-information theories of debt liquidity is difficult. For example, simply showing that bond liquidity declines as bond values deteriorate – in essence, regressing measures of bond liquidity on bond prices or credit spreads – suffers from a severe reverse causality endogeneity concern. Rather than deteriorations in bond value endogenously causing declines in liquidity, it could be that bond prices are deteriorating in response to exogenous changes in bond liquidity. Indeed, in analyzing the pricing implications of bond illiquidity a large literature regresses credit spreads on measures of liquidity – that is,. the exact opposite regression to that described above.[6]

In this paper we analyze the determinants of debt liquidity along two avenues. First, we test a series of predictions derived from the asymmetric-information theory of bond liquidity in Dang et al. (2012). These tests, in essence, present a series of empirical time-series and cross-sectional correlations in the data relating bond liquidity to observable bond and firm level characteristics. While in and of themselves, these empirical tests cannot rule out endogeneity concerns, taken together, they provide support to the single, parsimonious theory from which they are derived. In the second part of the paper, we alleviate endogeneity concerns using an instrumental variables (IV) approach (described below) to lend support for a causal relation between declines in bond values and diminished bond liquidity.

Our empirical analysis employs TRACE data on nonfinancial corporate bonds between July 2002 and December 2012, we employ three commonly used measures of bond liquidity: the γ measure based on Bao et al. (2011), the *Amihud* measure, and the Imputed Roundtrip Trades (IRT) measure (Feldhütter 2012).[7] We begin the analysis by confirming in our data that bond illiquidity rises as bond price declines. This well-known result is a basic prediction of the asymmetric information theory of bond illiquidity, and indeed of essentially all other theories of liquidity.[8] The economic effect is significant; a standard deviation fall in bond price, for example, is associated with increased illiquidity that ranges between 56.9 percent

[4]Myers and Majluf (1984) employ a distinction of a similar flavor in their Pecking Order Theory of capital structure in which debt is shown to be less informationally sensitive than equity.

[5]He and Milbradt (2014) provide a search-based model together with optimal firm default dynamics in which liquidity and default risk are endogenously determined. In their model, riskier bonds are more illiquid. Importantly, though, this result is driven by an exogenous assumption that bonds *in default* are illiquid – an assumption that can be justified using asymmetric-information primitives or, alternatively, an assumption regarding institutional differences regarding the market for defaulted bonds.

[6]See e.g., Chen et al. (2007), and Bao et al. (2011).

[7]All three measure *il*liquidity – that is, rises in the measure are associated with greater illiquidity.

[8]For studies showing a negative relation between bond illiquidity and credit spreads, see, e.g., Chen et al. (2007), Covitz and Downing (2007), Bao et al. (2011), de Jong and Driessen (2012), Dick-Nielsen et al. (2012).

and 78.9 percent of the unconditional mean of γ. The negative relation is robust to the inclusion of industry, issuing firm, and bond fixed effects, as well as year-by-month fixed effects, with the latter implying that the negative relation between price and illiquidity is not solely due to the fall in bond prices and concurrent rise in illiquidity that occurred during the 2008-9 financial crisis.

We proceed by testing a series of predictions stemming from the asymmetric-information theory of bond liquidity in Dang et al. (2012). First, we consider a more refined prediction of the theory – namely, that the hockey-stick relation in bond payoffs implies a nonlinear hockey-stick relation between bond illiquidity and bond price. This prediction is confirmed in the data: the negative relation between illiquidity and bond price exhibited in our baseline results is indeed highly nonlinear, exhibiting a hockey stick structure. In the lower deciles of bond price, illiquidity rises rapidly. We also confirm this hockey stick relation using credit ratings as well as Merton's Distance-to-default measure instead of bond prices.

Second, we show that when we control for current credit rating, bonds with a higher credit rating at issuance are *more* illiquid – consistent with a prediction of the asymmetric-information theory of bond liquidity based on Hanson and Sunderam (2013). According to this, bonds issued at a high rating do not develop a robust information-gathering infrastructure since market participants have little incentive to create one. As a consequence, when highly rated bonds become risky and enter the informationally sensitive region, the lack of information-gathering infrastructure increases adverse selection problems, thereby reducing liquidity. In contrast, bonds issued with a relatively low credit rating enjoy developed information-gathering environments, which diminish adverse selection and hence increase liquidity. Our results provide strong support for the Hanson and Sunderam (2013) hypothesis: when we hold constant the current credit rating of a bond, those bonds that declined from higher credit ratings exhibit *lower* liquidity. For example, bonds that deteriorate from a AA credit rating to a BB rating are less liquid than bonds that are issued at and remain with a BB rating.

Third, we show that, consistent with an asymmetric-information model, firms that are covered by more equity analysts have more liquid bonds and that the sensitivity of bond illiquidity to bond price is decreasing in the number of analysts covering the firm. As a fourth prediction, we examine how underlying collateral affects bond liquidity. Since collateral makes debt safer, expanding the range of the informationally insensitive region, theory predicts that secured bonds will be more liquid. This is precisely what the data show.

The fifth prediction we examine pertains to the effect of shifts in bond maturity on liquidity. The asymmetric-information theory of bond liquidity predicts that the regime shift from the information-sensitive region to the information-insensitive region will be more pronounced in bonds with shorter maturity. In-the-money short-maturity bonds are extremely safe (indeed, are almost like money) and hence are predicted to be extremely liquid. As bond value deteriorates, the debt becomes informationally sensitive and illiquidity rises rapidly. In contrast, in longer-maturity bonds this rise in illiquidity will be less pronounced since in-the-money long maturity bonds are riskier than their short-term equivalents and hence are less liquid. When the sample is segmented based on bond maturity, the data confirm this prediction. Bond illiquidity is more sensitive to reductions in bond price in shorter-maturity bonds. Further, the hockey-stick relation between illiquidity and bond price is far more pronounced in short-maturity bonds, precisely as predicted.

Sixth, we analyze the effect of changes in underlying equity volatility. The asymmetric-information theory of bond liquidity predicts that the sensitivity of bond illiquidity to bond price will be greater for bonds issued by more volatile firms. Using measures of implied equity volatility calculated from OptionMetrics, we confirm this result: the hockey-stick relation between bond illiquidity and bond price is substantially more pronounced in bonds of high-(implied) volatility firms.

In the second part of the paper, we use an instrumental variables (IV) approach to test a causal relation between declines in bond values and diminished bond liquidity. To be valid, an instrument must shift bond values without directly affecting bond liquidity.[9] We use three instruments that plausibly satisfy this requirement: the cumulative return in the stock of the firm issuing the bond since the first date the bond is traded in our data, the cumulative return of the equal-weighted portfolio of all stocks in the issuing firm's industry since the first date the bond trades, and an instrument measuring large price changes in the equity of the firm issuing the bond. Instrumenting for bond prices using all three instruments – effectively, movements in related equity returns – confirms the baseline finding that declines in bond price bring about increases in bond illiquidity. We confirm this result with a fourth instrumental variable – oil price movements – showing that oil price declines are associated with increases in illiquidity of bonds issued by oil and gas firms.

While the evidence presented herein supports the asymmetric-information theory of bond liquidity, there are clearly additional determinants affecting bond market liquidity. These include intermediary balance sheet strength, risk bearing capacity, and institutional differences across markets.[10] Still, our empirical analysis shows how informational asymmetries and

[9]Somewhat less formally, what is required are variables that shift firm (and hence bond) value, due to a fundamental change in firm cash flow.

[10]As one example, asymmetric information theories would find it difficult to explain differences in liquidity and credit spreads between on- and off-the run Treasuries (as in, e.g., Amihud and Mendelson, 1991) or between Treasuries and Refcorp Bonds (as in Longstaff, 2014).

changes in the degrees of bond safety have an economically meaningful effect in explaining liquidity in a manner consistent with the predictions of Dang, Gorton, and Holmström (2012). In addition, in robustness tests we show that our results continue to hold when focusing solely on investment grade bonds and when excluding the time-period of the 2008-09 financial crisis. The results due not appear, therefore, to be driven by institutional constraints precluding certain market participants from holding non-investment grade bonds or by weak intermediary balance sheets during a financial crisis.

Our paper relates to the ideas behind the literature on the money premium associated with safe assets (see, e.g., Stein 2012; Gorton and Metrick 2012; Krishnamurthy and Vissing-Jorgensen 2012; and Gorton 2016). Due to their high liquidity and extremely safe nature, highly safe assets provide moneylike services, which are valued by household and institutional investors alike. The literature shows empirically that investors are willing to pay a substantial money premium for highly safe assets, particularly those with short-term maturities.[11] Underlying reasons for this money premium include, but are not limited to, costs incurred by households in understanding investments in risky assets (Vissing-Jorgensen, 2003; Krishnamurthy and Vissing-Jorgensen 2012), the use of safe assets as collateral in financial transactions (Gorton 2010), and the use of Treasuries to back checkable deposits by commercial banks and money market funds (Bansal and Coleman 1996). While US government liabilities are clear examples of safe assets that provide security of nominal repayment, the safe asset literature argues that certain relatively safe and liquid debt instruments issued by the private sector can substitute in part for public debt in providing moneylike services.[12]

As in the safe assets literature, we focus on the relation among liquidity, asset safety, and bond prices. However, while the safe assets literature seeks to explain how safety and high liquidity affect bond yields, we focus on the *opposite* direction of causality: namely, how do variation in bond values and the degree of bond safety affect bond liquidity?[13] We seek, therefore, to explain the determinants of bond liquidity rather than the pricing implications of this liquidity. Our empirical tests rely on predictions from the theory of adverse selection of Dang et al., which relates the relative safety of a bond to its degree of information sensitivity and hence its liquidity. We empirically examine the relation among liquidity, safety, and bond

[11]For example, Krishnamurthy and Vissing-Jorgensen (2012) estimate a convenience premium on Treasuries of 73 bps. Greenwood et al. (2015) estimate a money premium of approximately 60 bps for one-week T-bills.

[12]Indeed, much of this literature focuses on the incentive of private actors, particularly in the financial sector, to capture the money premium by issuing relatively safe, short-term liabilities (see, e.g., Stein 2012; Greenwood et al. 2015; Carlson et al. 2016; and Sunderam 2016). Stein (2012) analyzes how such issuance may induce negative externalities with adverse affects on financial sector stability.

[13]Put differently and somewhat informally: whereas the literature on the money premium places bond prices on the lefthand side of the regression analysis, relating it to the supply of liquid, highly safe assets (see, e.g., Krishnamurthy and Vissing-Jorgensen 2012 and Greenwood et al. 2015), our analysis places liquidity on the left-hand side of the regression, relating it to plausible variation in the degree of bond safety.

values on a varying spectrum of the degree of bond riskiness, ranging from highly safe AAA bonds to bonds with very low credit ratings. Perhaps the closest paper to ours is Friewald et al. (2016) who develop and test a market-microstructure model of seniority and liquidity and show that more senior tranches of Asset-Backed Securities are indeed more liquid.

In addition, our paper is related to the large literature on the asset-pricing implications of liquidity, starting with Amihud and Mendelson (1986) and continuing with such studies as Aiyagari and Gertler (1991), Heaton and Lucas (1996), Vayanos and Vila (1999), Pastor and Stambaugh (2003), Acharya and Pedersen (2005), Sadka (2006), and Rocheteau (2010). This literature analyzes theoretically the premium that investors will pay for assets of greater liquidity and shows empirically that asset liquidity is indeed priced, with a sizable effect of liquidity on expected returns. Like the case of the safe assets literature, these studies focus on the pricing implications of liquidity rather than on the empirical determinants of liquidity, the focus of our study. One notable exception is Goldstein et al. (2007), who use the introduction of TRACE as a natural experiment to study the effects of transparency on liquidity in the corporate bond market. Similarly, Hameed et al. (2010) use a model of capital constraints and show that negative market and firm returns decrease stock liquidity.

The rest of the paper is organized as follows. Section 1 presents the data sources and explains the construction of the variables used in the analysis. Section 2 explores the relation between bond prices and liquidity. Section 3 presents the analysis of the cross-sectional relation among bond characteristics, informational sensitivity, and liquidity. Section 4 presents the instrumental variables analysis. Section 5 concludes.

1 Data Sources and Variable Definitions

1.1 Construction of illiquidity measures

We use bond-pricing data from the Financial Industry Regulatory Authority's TRACE (Transaction Reporting and Compliance Engine).[14] Our initial sample includes all corporate bonds traded in TRACE. Following Bao et al. (2011), we keep bonds with a time-to-maturity of at least six months and standard coupon intervals (including zero-coupon bonds). We exclude bonds that are issued by financial firms, as well as convertible, putable, and fixed-price callable bonds.

[14]The Financial Industry Regulatory Authority (FINRA) is a self-regulatory organization that is responsible for the collection and reporting of over-the-counter corporate bond trades.

We construct three measures of illiquidity. Our first measure, γ, has been proposed by Bao et al. (2011), and is defined as the negative covariance of log-price changes in two consecutive periods:

$$\gamma = -Cov(\Delta p_t, \Delta p_{t-1}). \tag{1}$$

Our second measure of illiquidity has been been suggested by Amihud (2002). The *Amihud* measure captures the effect of trading volume on return and is constructed by first calculating a daily average price impact measure:

$$\frac{1}{N_t} \sum_{i=1}^{N_1} \frac{|r_i|}{Volume_i}, \tag{2}$$

where N_t is the number of trades in a day, r_i is the return of trade i, and $Volume_i$ is the face value of trade i in millions of dollars. Next, we calculate a monthly *Amihud* measure by taking the median daily measure within a month.

Our third measure of illiquidity, the Implied Round-Trip Cost (IRT), is calculated by first identifying all trades in a particular bond with identical trading volumes within a trading date. Next, we calculate the scaled difference between the highest and lowest prices of these trades:

$$\frac{P_{max} - P_{min}}{P_{max}}, \tag{3}$$

where P_{max} and P_{min} are the highest and lowest prices paid for these same-volume transactions. We calculate a monthly IRT measure by calculating the mean daily measure within a month.

1.2 Summary statistics

We supplement the data from TRACE with bond characteristics from Thomson Reuter's SDC Platinum and Mergent FISD. Next, we augment the data using firm characteristics from Compustat, stock and industry returns from the Center for Research in Security Prices (CRSP), and measures of implied volatility from OptionMetrics. Our sample period in most of our empirical tests begins with the introduction of TRACE in July 2002 and extends through December 2012.

Table 1 reports summary statistics for our liquidity measures as well as for such bond characteristics as price, time to maturity, yield spread, Moody's rating, and amount of the outstanding face value. As the table shows, the mean bond price is 104, with an interquartile range of 99.06-109.2 and a standard deviation of 11.82. Bonds have an average of 8.7 years to maturity and an average spread that ranges from a 25th percentile of 0.897% to a 75th percentile of 2.58%, with a median of 1.51%. The mean current Moody's rating is Baa1, and the mean amount of bond outstanding is $367.4 million.

Table 1 also presents summary statistics for our three measures of illiquidity. The mean illiquidity measure γ is 1.533, and its interquartile range is between 0.136 (more liquid) and 1.460 (less liquid). The construction of the γ measure results in 178,971 bond-month observations from 2002 to 2012. The mean *Amihud* measure is 0.0119 and ranges from a 25th percentile of 0.00159 to a 75th percentile of 0.0131, and is available for 245,633 bond-month observations. Our third measure, IRT, is available for 248,920 bond-month observations, with a mean of 0.00256 and a standard deviation of 0.00353.

Figure 1 displays the behavior of the three illiquidity measures over time. We calculate the cross-sectional mean of each measure in every month and plot the time-series of the cross-sectional means from 2002 to 2012. As the three panels of Figure 1 demonstrate, illiquidity is high in 2002 but falls during the later months of 2002 and reaches its lowest level (high liquidity) during 2005 and 2006. The three panels also illustrate the dramatic increase in illiquidity during the financial crisis of 2008-9.[15]

To further gauge the behavior of aggregate bond illiquidity over time, Table 2 reports summary statistics for each of the three measures of illiquidity for three subperiods: 2002-6, 2007-9, and 2010-12. As Panel A shows, the median γ measure was 0.549, with an interquartile range of 0.147-1.692, while the *Amihud* and IRT means in 2002-6 were 0.0110 and 0.00257, respectively. Panel B of Table 2 shows that, consistent with Figure 1, illiquidity increased considerably between 2007 and 2009. For example, the mean γ measure in 2007-9 is 2.270 - representing an increase of 30.5 percent relative to 2002-6. Similarly, the *Amihud* measure increases by 23.6 percent and the IRT measure is 8.9 percent higher. The increase in illiquidity in 2008-9 is much higher if we exclude the year 2002, which is characterized by high illiquidity, from the earlier period. Illiquidity is down in 2010-12 – the γ measure declines by 64.1 percent from 2007-9 to 2010-12, while the *Amihud* and IRT measures decline by 14.7 percent and 15.7 percent, respectively.

2 Bond Prices and Liquidity

According to Dang, Gorton, and Holmström (2012), shifts in underlying firm value impact liquidity in debt markets. As underlying value deteriorates, debt shifts from being informationally insensitive to informationally sensitive as asymmetric information between market

[15] For an in-depth analysis of credit markets' illiquidity during financial crises, see Benmelech and Bergman (2018).

participants and adverse selection problems rise. Declines in bond prices thus lead to rises in bond illiquidity.[16]

Testing this mechanism is an extremely difficult endeavor. Simply regressing bond illiquidity on bond prices raises a fundamental reverse causality concern. Rather than declines in bond values causing illiquidity to rise, it could be that bond prices are declining due to an expected subsequent reduction in bond liquidity. Another concern is omitted variables – that is, factors correlated with both with bond illiquidity and bond prices.

We proceed, therefore, along two avenues. The first is to test a series of predictions stemming directly from the asymmetric-information theory of bond liquidity in Dang et al. (2012). Although the tests, in and of themselves, cannot rule out the endogeneity concerns above, taken together they lend support to the single, parsimonious theory from which they are derived.[17] In doing so, we emphasize that the evidence presented in support of the asymmetric-information theory of bond liquidity clearly does not rule out additional mechanisms affecting bond liquidity.

Our second avenue of research, presented below, is to alleviate endogeneity concerns using an instrumental variables (IV) approach. To be valid, an instrument must shift bond values without directly affecting bond liquidity.[18] We use three instruments that plausibly satisfy this requirement: (1) the cumulative return in the stock of the firm issuing the bond since the first date the bond is traded in TRACE; (2) the cumulative return of the equal-weighted portfolio of all stocks in the issuing firm's industry since the first date that the bond trades; and (3) an instrument measuring large price changes in the equity of the firm issuing the bond. Instrumenting for bond prices using all three approaches – effectively, movements in related equity returns – verifies our baseline finding: declines in bond price bring about increases in bond illiquidity. We confirm this result using a fourth instrumental variable – oil price movements – showing that oil price declines are associated with increases in illiquidity of bonds issued by oil and gas companies.

We begin our analysis by testing a series of predictions on the relation between bond liquidity and bond price derived from the asymmetric-information theory of bond liquidity.

[16] Information regarding underlying firm value is clearly also produced in equity markets as well. An implicit assumption, then, in asymmetric information theories of debt liquidity is that some form of market segmentation exists between equity and debt markets in that information between participants in the two markets does not flow seamlessly. Such segmentation can arise due to organizational constraints or constraints in the ability and willingness of participants in debt markets, such as insurance companies and pension funds, to analyze information on 'informationally-sensitive' assets.

[17] Alternatively, the results presented in this section present empirical evidence with which alternative theories should be consistent

[18] Somewhat less formally, what is required are variables that shift firm (and hence bond) value, due to a fundamental change in firm cash flow.

2.1 Baseline results

To document the empirical relation between bond illiquidity and prices, we estimate variants of the following baseline specification:[19]

$$Illiquidity_{i,t} = \alpha + \beta_1 \times Price_{i,t-1} + \beta_2 \times \mathbf{X}_{i,t-1} + \boldsymbol{\delta_t} + \boldsymbol{\theta_i} + \epsilon_{i,t}, \tag{4}$$

where *Illiquidity* is one of our three measures: γ, *Amihud*, and *IRT*, subscripts indicate bond (i) and month (t), $Price_{i,t-1}$ is bond price or the yield spread over a maturity-matched Treasury lagged by one month, $\mathbf{X_i}$ is a vector of bond characteristics that include the issue size and time since issuance, δ_t is a vector of either year or year-by-month fixed effects, θ_i is a vector of cross-sectional fixed effects – industry (three-digit SIC), firm, or bond fixed effects – and $\epsilon_{i,t}$ is the regression residual. We report the results from estimating variants of regression 4 in Table 3. Tables throughout this paper report regression coefficients and standard errors clustered at the bond level (in parentheses).

Table 3 reports the coefficients from estimating regression 4 using the γ measure of illiquidity as the dependent variable. The main explanatory variable in the first six columns is the bond yield spread, and in Columns 7-12 it is price. As can be seen, the table confirms a well-known result in the literature on liquidity: bond illiquidity is negatively related to bond price (and positively related to bond yields).

Column 1, based on regression 4 and estimated with year and industry fixed effects, shows a positive association between illiquidity and yield spread. We obtain very similar results when we include year-by-month – instead of just year fixed effects – and industry fixed effects (Column 2). The year-by-month fixed effects imply that this relation is not driven simply by variation in risk-free rates over time, or variation in any other component of credit spreads common to all bonds in a given year-month. Similarly, these year-by-month fixed effects also imply that the relation presented here, as well as those described below, are not driven simply by the rise in illiquidity during the 2008-9 financial crisis.

Next, Columns 3 and 4 of Table 3 show that the results hold whether we include both firm and year fixed effects (Column 3) or firm and year-by-month fixed effects (Column 4). Finally, in Columns 5 and 6 we control for time-invariant bond fixed effects – effectively identifying off of within-bond time-series variation in addition to year fixed effects (Column 5) and year-by-month fixed effects (Column 6). The positive association between γ and yield spread remains positive and significant at the 1 percent level when we control for bond fixed effects.

[19] As our left-hand side measures are positively correlated with bond *il*liquidity, we refer throughout the paper to bond illiquidity rather than bond liquidity.

The economic effect of the yield spread on γ is sizable: a one standard deviation increase is associated with increased illiquidity between 56.9 percent and 78.9 percent of γ's unconditional mean. Moving from the 25th percentile to the 75th percentile results in increased illiquidity that is between 15.5 percent and 21.5 percent of the unconditional mean.[20]

In Columns 7-12 of Table 3 we use bond price as our variable of interest in explaining γ. Column 7 is estimated with year and industry fixed effects. As can be seen, there is a negative correlation between illiquidity and bond price, implying that bonds with lower prices have a high γ measure of illiquidity. As in the first six columns, we obtain similar results when we include: year-by-month – instead of just year – and industry fixed effects (Column 8); both firm and year fixed effects (Column 9); firm and year-by-month fixed effects (Column 10); bond and year fixed effects (Column 11); and bond as well as year-by-month fixed effects (Column 12). Turning to the economic effect of bond prices on γ, moving from the 25th percentile to the 75th percentile results in increased illiquidity that is between 54.2 percent and 83.4 percent of the unconditional mean of γ. We obtain similar results when we use the *Amihud* measure of illiquidity as the dependent variable and report the results in Table 4. In unreported results we repeat the analysis in Tables 3 and 4 using the IRT measure of illiquidity and find similar values.

2.2 Robustness Tests

Controlling for Volatility

One concern with the results presented in Tables 3 and 4 is that our findings are driven by volatility. For example, Brunnermeier and Pedersen (2009) predict that market liquidity declines as volatility increases, especially when capital markets are distressed. Similarly, Stoll (1978), Grossman and Miller (1988), and Vayanos (2004) show that volatility and liquidity are linked. Table 5 presents a correlation matrix between our three measures of illiquidity and two measures of volatility: (1) implied equity volatility – which we extract from the volatility surface files in OptionMetrics – calculated from option prices on the traded stock of the issuer of each bond; and (2) bond volatility defined as the standard deviation of daily bond returns in a given month.[21] As Table 5 illustrates, implied volatility is positively correlated with our three measures of illiquidity with a Pearson correlation coefficient that ranges from 0.157 to 0.293 (all statistically significant at the 1 percent level). While our measure of bond volatility

[20]The distribution of the yield spread is highly skewed, and hence the effect of one standard deviation is considerably higher than the effect of an interquartile range change.

[21]We use at-the-money call and put options' implied volatilities with a delta of 0.5 and an expiration of 30 days.

is also correlated with the three measures of illiquidity – its correlations with the measures are much smaller, ranging from 0.015 to 0.026.

We reestimate regression 4 adding the two measures of volatility as explanatory variables and report the results in Table 6. As Table 6 illustrates, implied volatility is positively correlated with bond illiquidity – while bond volatility is not significantly related to illiquidity. The mean implied volatility in our sample is 0.305, and a one standard deviation increase in implied volatility results in increased illiquidity of 13.3 percent relative to the unconditional mean when we include year and firm fixed effects (Column 3). Importantly, the negative correlation between bond price and illiquidity remains significant while the magnitude of the effect of bond price on illiquidity is slightly lower – for example, with both firm and year fixed effects the coefficient changes from -0.093 to -0.081. In summary, our findings are robust to the inclusion of implied volatility and bond volatility and are unlikely driven by an omitted variable related to volatility.

Bond Illiquidity and the 2008-09 Financial Crisis

Another concern with our results is that they are driven by the financial crisis period of 2008-09. According to this, sharp bond price declines during the crisis may have forced institutional investors to sell off portions of their bond portfolios, thereby resulting in bond market illiquidity. We address this concern in the remaining columns of Table 6. Column 7 of Table 6 presents results from reestimating regression 4 for the non-crisis years – i.e., we run the regression pooling together the 2002-07 and 2010-12 periods but excluding the 2008-09 period. As the table shows, the negative relation between γ and lagged price remains negative and significant at the one percent level. The magnitude of the effect of bond price on illiquidity is lower in non-crisis years – for example, with both bond and year-by-month fixed effects the coefficient changes from -0.112 to -0.077. Indeed, when we estimate regression 4 solely for the 2008-09 crisis period, the coefficient on γ jumps to -0.172. This increased sensitivity between illiquidity and bond price during the financial crisis is very much consistent with additional factors such as intermediary balance sheet strength, risk bearing capacity, and institutional constraints increasing in importance during the crisis. Nevertheless, as Table 6 demonstrates, the results continue to hold outside of the financial crisis as well.

Institutional Investors and Investment Grade Rating

An additional concern is that our results are driven by various market participants that are legally required to hold investment-grade bonds in their portfolios. Declines in bond prices, together with associated downgrades across the investment-grade threshold, may lead to bond illiquidity. We address this concern directly in the last two columns of Table 6 in which we estimate regression 4 separately for investment grade (Column 9) and non-investment grade bonds (Column 10). As can be seen, the negative relation between lagged price and illiquidity holds in both investment grade and non-investment grade bonds.[22]

3 The Asymmetric Information Theory of Bond Liquidity: Reduced Form Evidence

Having established the baseline result of a negative relation between bond illiquidity and bond price, we present a series of empirical tests pertaining to predictions stemming from the asymmetric-information theory of bond liquidity of Dang et al. (2012).

3.1 Liquidity and bond prices: A "hockey-stick" relation

Beyond the negative relation between bond illiquidity and bond price, an important prediction of the informational theory of bond liquidity is that this relation exhibits a nonlinear hockey-stick-like shape. Moving from high to low bond prices increases illiquidity, but the effect should be larger at lower bond prices. Indeed, at low bond prices, payoffs are concentrated within the "informationally sensitive" region of the concave payoff structure of bonds, implying high uncertainty and adverse-selection frictions that are predicted to increase bond illiquidity. In contrast, declines in bond values in the informationally insensitive region should be associated with relatively small increases in bond illiquidity.

To test the prediction of a nonlinear effect, we regress our measures of bond illiquidity on indicator variables for the 10 deciles of bond price. Specifically, we run the following regression:

$$Illiquidity_{i,t} = \beta_0 + \sum_{k=1}^{10} \beta_k \times PriceDecile^k_{i,t-1} + \mathbf{b}_i\gamma + \mathbf{c}_t\delta + \epsilon_{i,t}, \tag{5}$$

where *Illiquidity* is one of three measures of bond illiquidity, γ, $Amihud$, or IRT, for bond i in month t. *PriceDecile* is a set of 10 indicator variables based on the (within-year) deciles of bond price – $PriceDecile^k_{i,t-1}$ equals one if bond i is in price decile k at month $t-1$.[23] b_i is a

[22] We use the standard definition of investment grade which includes a bond rating of BBB- and above. Our results hold when we define investment grade as BBB+ and higher, or A- and higher.

[23] Price decile 1 represents bonds with the lowest price.

vector of bond fixed effects, and c_t is a vector of either year or year-by-month fixed effects.[24] Standard errors are clustered at the bond level. The results are reported in Table 7.

Similar to the results documented in Tables 3 and 4, we find a negative relation between price and illiquidity across all three measures of bond liquidity. Importantly, the coefficients on the 10 price decile variables present a nonlinear relation between bond prices and illiquidity. Focusing on Column 2, which employs γ as the dependent variable along with year-by-month fixed effects, we see that a rise from price decile 1 (the lowest decile in the regression) to price decile 2 reduces γ by 1.289 units (as compared to a sample mean of 1.533). In contrast, moving from price decile 9 to price decile 10 reduces γ measure by only 0.079 (=2.455-2.376). As Table 7 demonstrates, the results using the other two measures of bond liquidity are similar (Columns 3-6).

Figure 2 provides a graphical representation of the nonlinear relation between price and illiquidity. To create the figure, we rerun regression 5 relating γ to bond price, but use indicator variables based off of 20 equal-sized price bins rather than 10 equal-sized bins (that is, deciles).[25] As in equation 5, the regression is estimated with bond and year-by-month fixed effects. Figure 2 then plots the coefficients on the resulting price bins. The predicted nonlinear, hockey-stick relation between illiquidity and price is readily observable, with the lower five price bins exhibiting the highest increases in bond illiquidity.

3.2 Liquidity and Distance to Default

Figure 3 provides an additional representation of the nonlinear hockey-stick behavior of bond illiquidity, using Merton's Distance-to-default – a structural measure for default risk based on the Merton model – as the left-hand side variable measuring the degree of bond distress. We construct the Distance-to-default measure following Campbell, Hilscher et al.(2008), Bao, Chen, Hou, and Lu (2015), and Bao and Hou (2017).[26] Figure 3 is constructed in a manner similar to Figure 2, but bond price is replaced by Distance-to-default. That is, we run a variant of regression]5 using 20 indicator variables based off of 20 equal-sized bins of Distance-to-default. As in equation 5, the regression is estimated with bond and year-by-month fixed effects. Figure 3 plots the coefficients on the resulting Distance-to-default bins. As in Figure 2, the predicted nonlinear, hockey-stick relation between illiquidity and

[24]Note that with the inclusion of bond fixed effects, the regression is identified off of changes over time in the level of illiquidity and bond price for each bond.

[25]20 bins are used solely to obtain a finer picture of the nonlinear relation. Results are similar using deciles.

[26]Distance-to-default incorporates information on both the value of firm assets compared to debt obligations and the volatility of assets.

distance-to-default is readily observable in Figure 3 as. In this case, bonds in the two lowest Distance-to-default bins exhibit large increases in bond illiquidity.

3.3 Liquidity and credit ratings

Analyzing the relation between bond illiquidity and credit ratings is another way to view the nonlinear behavior of liquidity within the bond market. To analyze this relation we group credit ratings into seven categories, with Category 1 encompassing Moody's credit ratings between Aaa and Aa3 (inclusive), Category 2 encompassing ratings between A1 and A3, and so on.[27] We then regress the γ measure of bond illiquidity on indicator variables defined using the seven rating categories. Regressions include industry, firm, or bond fixed effects, as well as year or year-by-month fixed effects. The results are shown in Table 8. Consistent with higher uncertainty regarding underlying value, bond illiquidity decreases with credit rating. Importantly, similar to the results above, the relation exhibits a strong nonlinear effect, with illiquidity rising substantially in Categories 6 and 7. Figure 4 provides a graphical representation of the relation between bond rating and illiquidity, depicting the average illiquidity for each Moody's ratings category.[28]

Next, we examine a prediction of the asymmetric-information theory of bond liquidity based on Hanson and Sunderam (2013). According to their model, market incentives to build an "information production infrastructure" when analyzing relatively safe debt securities will be weak because market participants will are likely obtain only a small informational advantage in trading such assets. As a consequence, when the default risk of highly rated bonds rises, the informational infrastructure meant to reduce asymmetric information is lacking, and further, because this infrastructure takes time to develop, trading in such debt instruments will suffer from adverse selection. In contrast, bonds issued with a low rating will enjoy a more developed information-gathering environment from the outset. Thus, based on Hanson and Sunderam (2013), a natural prediction of the information-asymmetry theory of bond liquidity is that, holding constant the current credit rating of a bond, those issued at a *higher* credit rating should be *less* liquid.

To test the prediction, we mark each bond's S&P credit rating at any point in time.[29] We then regress our illiquidity measures on the *change* in credit rating from the bond's previous rating to its current rating while controlling for current credit rating. We use the entire rating distribution for this test and assign a value of 1 to a rating of AAA, 2 to AA+, 3 to AA, and

[27] Category 3 includes ratings between Baa1 and Baa3, Category 4 between Ba1 and Ba3, Category 5 between B1 and B3, Category 6 between Caa1 and Caa3, and Category 7 ratings Ca and C.

[28] The figure is plotted by calculating sample means of the γ measure for each rating category.

[29] We obtain the initial credit rating for each bond by matching TRACE data to SDC Platinum data.

so forth to the lowest rating category of D, which is assigned a value of 22. Specifically, we run the following regression:

$$\begin{aligned} Illiquidity_{i,t} &= \beta_0 + \zeta \times \Delta Rating_{i,t-1} + \psi Time\,elapsed_{i,t-1} + \chi \Delta Rating_{i,t-1} \times Time\,elapsed_{i,t-1} \\ &+ \sum_{k=1}^{7} \beta_k \times Rating\,Category^{k}_{i,t-1} + \mathbf{b}_i\gamma + \mathbf{c}_t\delta + \epsilon_{i,t}, \end{aligned} \tag{6}$$

where $\Delta Rating$ is the bond-level difference between the previous credit rating and the current (lagged $t-1$) credit rating: $\Delta Credit\,Rating_{i,t-1} = Credit\,Rating_{i,t-1} - Credit\,Rating_{i,previous}$. A positive $\Delta Rating$ implies that the bond has been downgraded in its last rating action. The regressions are run with current rating, bond, and year-by-month fixed effects.

The results are shown in Table 9. As seen in Column 1, the coefficient on the change in credit rating is positive and significant. As predicted, controlling for current rating, if the drop from the previous rating to the current rating is larger, the bond is more illiquid. Consistent with incentives for"information production infrastructure" in Hanson and Sunderam (2013), the trajectory of bond ratings is related to bond illiquidity, above and beyond the current rating. One concern with the results presented in Table 9 is that rating agencies may tend to smooth rating changes over time, leading to a "rating momentum" phenomenon in which a recent downgrade contains information on future expected downgrades (Lando and Skødeberg 2002). Such a momentum effect would imply that our results may be driven by expected future deterioration in credit quality rather than by information production. To alleviate the concern about rating momentum, we add lagged bond price to our regression. To the extent that rating agencies exhibit rating momentum bond market prices should reflect and adjust to such information. As Column 2 of Table 9 shows, after controlling for bond prices, the coefficient of $\Delta Credit\,Rating_{i,t-1}$ is still statistically significant at the 1 percent level, although its magnitude reduces from 0.237 to 0.106. Nevertheless, the economic magnitude of $\Delta Credit\,Rating_{i,t-1}$ is still sizable – holding constant current credit rating, a downgrade of three notches increases illiquidity by 0.318, representing an increase of 20.7 percent relative to the unconditional illiquidity mean. Column 3 adds the two measures of volatility used in Table 6, in addition to the bond price, and the coefficient of $\Delta Credit\,Rating_{i,t-1}$ remains significant.

In Columns 4-6 we add to the change in bond credit rating, $\Delta Credit\,Rating$, the time (in months) that elapsed since the previous rating, as well as the interaction between $\Delta Credit\,Rating$ and the time that elapsed since the rating change. We hypothesize that as time elapses, an informational infrastructure for downgraded bonds will be created, and thus illiquidity should decrease over time. As Columns 4-6 of Table 9 demonstrate, we find that the coefficient on the interaction term χ is negative, suggesting that, controlling for the current credit rating, the effect of a downgrade on illiquidity does indeed decay over time.

3.4 Liquidity and Analyst Coverage

We next turn to test the relation between informational infrastructure and bond illiquidity more directly using data on analyst coverage. We use the number of equity analysts covering the firm issuing the bond as a proxy for the degree of asymmetric information among bond market participants.[30] In particular, we hypothesize that when there are more equity analysts, more public information will be produced on the underlying firm value supporting the bond, which implies in turn that the bond should become more liquid. Implicit in the hypothesis relating analyst equity coverage to information asymmetries in bond markets are one of the following two assumptions: (1) equity and bond markets are not completely segmented in that at least some information produced by equity-analysts flows between the two markets; or (2) the degree of analyst equity coverage is positively correlated with the degree of information produced by participants in bond markets.[31]

Using analyst coverage as a proxy for information asymmetries, we test two predictions of the asymmetric-information theory of bond illiquidity. The first is simply that bond illiquidity should be negatively associated with analyst coverage. The second, more nuanced prediction is that decreases in the sensitivity of bond illiquidity to bond price should be *decreasing* in the number of analysts covering the firm. With greater analyst coverage, bonds entering the informationally sensitive region of debt should have a smaller impact on bond illiquidity, as analysts' information production reduces market information asymmetries.

To test these two predictions, we regress the Gamma measure of bond illiquidity on indicator variables defined from five (equal-sized) quintiles of analysts' coverage as well as their interactions with lagged price:

$$\begin{aligned} Illiquidity_{i,t} &= \alpha_0 + \alpha_1 \times Price_{i,t-1} + \sum_{k=1}^{5} \beta_k \times Analysts\,Coverage^k_{i,t} \\ &+ \sum_{s=1}^{5} \zeta_s \times Analysts\,Coverage^k_{i,t} \times Price_{i,t-1} + \mathbf{b}_i \xi + \mathbf{c}_t \delta + \epsilon_{i,t}, \end{aligned} \tag{7}$$

[30] The number of analysts is obtained from I/B/E/S.

[31] Of course, we maintain the plausible assumption required in asymmetric-information theories of debt that information flows between debt and equity markets are not perfect: participants in debt markets cannot fully benefit from all information produced in equity markets.

where *Illiquidity* is the γ measure of bond illiquidity for bond i in month t, $Price_{i,t-1}$ is the one-month lagged bond price, and $Analysts\,Coverage$ is a set of five indicator variables constructed from equal-sized quintiles of the number of analysts covering the bond. We report the results in Table 10.

All regressions are run with time fixed effects (either year or year-by-month) as well as bond fixed effects. Bond fixed effects imply that identification is achieved from variation over time in the number of analysts covering the firm. This alleviates concerns that cross-sectional correlations between analyst coverage and various firm characteristics – such as firm size – are driving the results.

As Table 10 shows, the two predictions are borne out in the data. First, the number of analysts covering the firm is negatively correlated with bond illiquidity. That is, consistent with an asymmetric-information theory of liquidity, bonds issued by firms with greater analysts coverage are more liquid. Further, we also find evidence supporting the second prediction that the sensitivity of bond illiquidity to bond price is decreasing in the number of analysts covering the firm. As the table illustrates, while lagged price is negatively related to bond illiquidity, the effect of lagged price on illiquidity is diminished for bonds with more analysts covering their firms. Indeed, based on the coefficient on the interaction term between the highest quintile of analyst coverage and bond price in Column 2 of the table (with bond and year-by-month fixed effects), the sensitivity of illiquidity to declines in bond prices is approximately 40 percent smaller among bonds in the highest quintile of analyst coverage as compared to bonds in the lowest quintile of analyst coverage.[32]

3.5 Collateral and liquidity

As another test of the asymmetric-information theory of liquidity, we examine the role played by collateral in determining bond liquidity. Controlling for the probability of default, theory predicts that collateral serves to increase liquidity because it supports bond payoffs in the event of default, making such payoffs less sensitive to private information regarding the distribution of firm cash flows. To test for this, we use SDC's security description to construct an indicator variable that takes on the value of one if a bond is secured by collateral and zero otherwise. Although the SDC security description is lacking for many bonds, we are able to classify more than 600 secured and unsecured bonds that account for 20,474 bond-month observations. We then regress each of the three illiquidity measures on the secured bond indicator variable as well as on firm and year fixed effects and the seven credit

[32] The coefficient on lagged bond price for Quintile 1 of analyst coverage (the omitted quintile) is -0.13, while the total differential on lagged bond price in Quintile 5 of analyst coverage is -0.08 = -0.13 + 0.05.

rating indicator variables used in Table 9. The results are presented in Table 11. Consistent with the hypothesis, and similar to Friewald et al. (2016) we find that secured bonds are indeed more liquid than unsecured bonds, controlling for firm, year, and rating fixed effects. The effect is economically significant: as shown in Column 1 of Table 11, secured bonds have a Gamma illiquidity measure that is on average lower by 0.895 than that of unsecured bonds issued by the *same* firm. Bond collateral thus reduces illiquidity by 58.4 percent relative to the sample unconditional mean of 1.533.

3.6 Liquidity, bond prices, and bond maturity

In this section we analyze the relation between bond maturity and bond liquidity in light of the asymmetric-information theory of bond liquidity. We begin by confirming a basic result well known in the literature: longer-maturity bonds are more illiquid. Longer time to maturity should be associated in general with greater uncertainty over underlying value. When trading such bonds, information-asymmetry and adverse selection problems should thus be greater, and hence illiquidity should be larger as well – Indeed, Bao et al. (2011) show that longer-term corporate bonds are more illiquid.

To analyze the relation between bond maturity and illiquidity, we regress the Gamma measure of bond liquidity on indicator variables defined from five (equal-sized) quintiles of bond maturity, running the following specification:

$$Illiquidity_{i,t} = \beta_0 + \sum_{k=1}^{5} \beta_k \times MaturityQuintile^k_{i,t} + \mathbf{b}_i\gamma + \mathbf{c}_t\delta + \epsilon_{i,t}, \tag{8}$$

where *Illiquidity* is the γ measure of bond illiquidity for bond i in month t, and $MaturityQuintile^k_{i,t}$ is a set of five indicator variables based on quintiles of bond time to maturity – that is, $MaturityQuintile^k_{i,t}$ equals one if bond i is in maturity quintile k at month $t-1$.[33] $\mathbf{b}_i$ is a vector of industry, issuing firm, or bond fixed effects, and c_t is a vector of either year or year-by-month fixed effects. Standard errors are clustered at the bond level.

The results are shown in Table 12. Longer maturity bonds are indeed more illiquid, as theory predicts. This result holds across different fixed-effect specifications – industry, firm, and bond – with bonds in the fifth quintile of maturity exhibiting a γ measure of illiquidity that is higher by 1.46 on average than bonds in maturity quintile 1.[34]

We continue by examining a more specific prediction of the asymmetric-information view of bond liquidity. In particular, the theory predicts that the sensitivity of illiquidity to bond

[33] Quintile 1 represents bonds with the shortest maturity.

[34] This estimate is based on Column 6, which employs bond and year-by-month fixed effects.

price will be greater among shorter-maturity bonds as compared to bonds of longer maturity. To see this, note first that when bonds are distressed, the value of the underlying asset – that is, the firm – is in the informationally sensitive region, and hence bond illiquidity should be high. This rise in illiquidity of distressed bonds should occur regardless of bond maturity. In contrast, theory predicts that the illiquidity of short- and long-maturity bonds will behave very differently when bond values are high and far from distress. Indeed, in short-maturity bonds, a high value of the underlying asset (that is, firm value) compared to the level of debt outstanding implies that the probability that the bond will become distressed – that is, enter the informationally sensitive region where illiquidity is high – is relatively small. Thus, short-maturity bonds far from distress should be very liquid.

In contrast, in longer-maturity bonds, even if firm value is high compared to debt level, a longer maturity implies a significantly probability that adverse shocks will push the bond into the distressed, informationally sensitive region. Thus, longer-maturity bonds should be relatively illiquid even when bond prices are high. Since both short- and long-maturity bonds are predicted to be illiquid when bond values are low, the end prediction, therefore, is that the sensitivity of bond illiquidity to bond price should be lower among longer-maturity bonds.

To test this prediction, we rerun regression 5 separately for each of the five maturity quintiles. All regressions focus on the γ illiquidity measure and employ bond and year-by-month fixed effects with standard errors clustered at the bond level. Consistent with the prediction, Table 13 shows that the sensitivity of bond illiquidity to price is indeed smaller in longer-maturity bonds. For example, within the shortest-maturity quintile, moving from the lowest to the highest price decile increases the γ by 3.013. In contrast, within the longest-maturity quintile, the same change results in an increase of 1.785 in the γ illiquidity measure.

Figure 5 presents the relation between bond illiquidity and price by maturity quintile. To construct the figure, we rerun regression 5 for each of the five maturity quintiles using indicator variables constructed from 20 equal-sized bins of bond price (with bond and year-by-month fixed effects). The coefficients are plotted on the 20 price-bin indicator variables.[35]

As can be seen, the figure is highly consistent with the predictions of the asymmetric-information theory of bond liquidity. In both short- and long-maturity bonds, illiquidity is high among the low bond-price deciles. In contrast, in *short*-maturity bonds, high deciles of bond price are extremely liquid, consistent with the low probability that these bonds will

[35] The figure plots the average effect for each price bin using the average of the coefficients of the year-by-month fixed effects. Put differently, for each price bin we add the coefficient on the price-bin indicator to the average coefficient on the temporal fixed effects.

enter distress before maturity. High deciles of bond price in *long*-maturity bonds are far more illiquid, consistent with the greater likelihood that these bonds will enter the informationally sensitive region before maturity.

3.7 Liquidity, bond prices, and equity volatility

As discussed above, and confirmed in Table 6, bond illiquidity increases with the volatility of the issuing firm's equity. This well-known result is, of course, consistent with the asymmetric-information theory of bond liquidity: all else equal, increased volatility raises the probability that the bond will become distressed, with payoffs falling within the informationally sensitive region. Bond illiquidity should thus be higher when equity volatility rises.

A second, more specific, prediction of the asymmetric-information theory of bond illiquidity is that the sensitivity of bond illiquidity to bond price should be *decreasing* in the issuing firm's equity volatility. To see this, it is useful to consider the extreme case where equity volatility is near zero, so that there is little uncertainty in the underlying asset. When this is the case, even when the bond is distressed and the likelihood of default is high, there will be no asymmetric information regarding the underlying value of the bond: the volatility of the underlying asset is extremely low, and hence there should be little uncertainty regarding the bond's true value. Put differently, even when bond prices drop into the distressed region where bond payoffs depend on the value of the underlying asset, both buyer and seller are relatively certain of the value of the bond because underlying uncertainty is low. In contrast, when equity volatility is relatively high, liquidity is predicted to depend greatly on whether the bond is in the informationally sensitive or insensitive regions. Indeed, as the bond price rises and the value of the firm enters the informationally insensitive region, liquidity is predicted to rise since bond payoffs will not be very sensitive to the realization of the underlying value of the firm.

To test the prediction that illiquidity is less sensitive to bond price when underlying uncertainty is low, we regress γ on the interaction between the bond-price level and equity implied volatility. Specifically, we run the following regression:

$$\begin{aligned} Illiquidity_{i,t} &= \alpha_0 + \alpha_1 \times Price_{i,t-1} + \sum_{k=1}^{5} \beta_k \times Implied\,Vol\,Quintile^k_{i,t} \\ &+ \sum_{s=1}^{5} \zeta_s \times Implied\,Vol\,Quintile^k_{i,t} \times Price_{i,t-1} + \mathbf{b}_i \xi + \mathbf{c}_t \delta + \epsilon_{i,t}, \end{aligned} \tag{9}$$

where *Illiquidity* is the γ measure of bond illiquidity for bond i in month t, $Price_{i,t-1}$ is the one-month lagged bond price, and $Implied\,Vol\,Quintile$ is a set of five indicator variables constructed from equal-sized quintiles of implied equity volatility – that is, $Implied\,Vol\,Quintile^{k}_{i.t}$ equals one if bond i is in implied volatility quintile k at month $t-1$.

The results are shown in Table 14. First, consistent with the results in Table 6, we find that illiquidity rises with underlying equity volatility. Second, consistent with our results throughout, illiquidity declines with bond price. Importantly, and consistent with the asymmetric-information theory of bond liquidity, the table shows that the sensitivity of bond illiquidity to bond price increases with underlying equity volatility. Inspecting the interaction coefficients in Table 14 shows that the sensitivity of γ to bond price in the highest implied equity volatility quintile is 2.7 times larger than the sensitivity of γ to bond price in the lowest equity volatility quintile.[36]

Figure 6 provides a graphic representation of this result. To construct the figure, we run regression 5 – the baseline regression relating γ to ten indicator variables constructed from the ten deciles of bond price – on three separate subsamples of the data: (1) bonds in the lowest decile of equity implied volatility; (2) bonds in decile 5 of equity implied volatility; and (3) bonds in the highest decile of equity implied volatility.[37] The coefficients on the price deciles are then plotted for each of the three regressions. The results are consistent with the asymmetric-information theory of bond liquidity. Among bonds in the lowest decile of equity volatility, bond illiquidity is low and insensitive to bond price. As described above, with little underlying volatility, uncertainty and asymmetric information are low regardless of the bond price level. As compared to decile 1, bonds in decile 5 of implied equity volatility exhibit higher illiquidity as well as a higher sensitivity of illiquidity to bond price. Finally, among bonds in the highest decile of implied equity volatility, bond illiquidity is both high and extremely sensitive to bond price. Indeed, as predicted, the hockey-stick relation between illiquidity and bond price is most pronounced for bonds in this decile, with illiquidity rising substantially in the lowest three deciles of bond prices.

[36] Focusing on Column 6, which includes bond and year-by-month fixed effects, the coefficient on bond price is -0.054 for the lowest equity implied volatility quintile, whereas it is -0.1456 for bonds in the highest quintile of equity-implied volatility.

[37] All regressions include bond and year-by-month fixed effects.

4 Instrumental Variables Regressions of Liquidity on Prices

In this section, we employ an instrumental variable approach to analyze the relation between bond prices and bond liquidity. Whereas prior literature analyzing the asset pricing implications of liquidity regresses yield spreads on bond liquidity, our focus is on the determinants of bond liquidity and, in particular, how underlying bond values affect bond liquidity. Hence, the regressions we analyze take the exact opposite form to those employed in the asset-pricing literature: bond liquidity is the dependent variable and bond prices or yields are the explanatory variable. The results presented in Tables 3 and 4 and the additional tests in Tables 7-14 present a strong negative correlation between illiquidity and bond prices in line with the asymmetric information theory of bond liquidity. Still the estimates are subject to endogeneity and reverse causality concerns. Rather than declines in bond values causing illiquidity to rise, it could be that bond prices are declining due to an expected (future) reduction in bond liquidity. While throughout the paper we estimate variants of regression 4 using lagged values of yield spreads and bond prices, it is of course still possible that lagged bond prices contain information on future liquidity, thereby maintaining the reverse causality concern. We thus address the reverse causality concern through an instrumental variables (IV) approach.

4.1 Cumulative stock and industry returns

We start by using the return on the equity of the firm that issued the bond as an instrument for its bond price. We argue that the return of the firm's stock is unlikely to be driven by concurrent bond liquidity and is thus not subject to the reverse causality concern. Theoretically, the sign of the correlation between the firm's stock and bond returns is ambiguous. On one hand, the value of the firm's assets affects the value of the firm's bonds and stocks in the same direction, resulting in a positive relation between stock returns and bond prices. On the other hand, the variance of the firm's assets leads to opposite effects on the value of firm debt and equity. The empirical evidence suggests that the first effect – which predicts a positive correlation between stock returns and bond prices – dominates the second, variance-based effect. For example, Kwan (1996) regresses weekly changes in individual bond yields on the issuing firm's lagged stock returns and finds that bond returns are significantly and negatively correlated with lagged stock returns – implying a positive correlation between lagged stock returns and bond prices.

Before running two-stage regressions, we begin by estimating the following reduced form specification:

$$Illiquidity_{i,t} = \alpha + \beta_1 \times Cret_{i,t-1} + \beta_2 \times \mathbf{X}_{i,t-1} + \boldsymbol{\delta_t} + \boldsymbol{\theta_i} + \epsilon_{i,t}, \tag{10}$$

where *Illiquidity* is the γ measure, subscripts indicate bond (i) and month (t), $Cret_{i,t-1}$ is the lagged cumulative return on the stock of the issuing firm since the first date that the bond is traded in TRACE, $\mathbf{X_i}$ is a vector of bond characteristics that includes the bond's issue size and time since issuance, δ_t is a vector of either year or year-by-month fixed effects, θ_i is a vector of cross-sectional fixed effects – either firm or bond fixed effects – and $\epsilon_{i,t}$ is the regression residual. We report the results from estimating variants of regression 10 in Table 15. We define $Cret_{i,t-1}$ as a cumulative return variable so as to: (1) enable identification off of large changes in stock prices that may shift bond values across the informationally sensitive and insensitive regions; and (2) avoid a weak instruments problem. We also use large lagged monthly returns as an instrument in the next subsection.

As the first column of Table 15 illustrates, cumulative stock returns have a statistically significant negative effect on γ, implying that higher stock returns lead to higher bond liquidity (i.e., lower γ). The estimate of β_1 is -0.281 (Column 1 with bond and year-by-month fixed effects) and is statistically significant at the 1 percent level. As stock returns and bond prices are positively related in the data (Kwan 1996), the reduced form result supports the hypothesized mechanism: higher stock returns are associated with higher bond prices, which in turn leads to higher bond liquidity.

In Column 2 of Table 15 we use a different instrument, defined as $Industry\,Cret_{i,t-1}$, the lagged cumulative return on an equal-weighted portfolio of all the stocks in the issuing firm's industry since the first date that the bond is traded in TRACE.[38] The underlying idea in this industry-based instrument is that lagged stock returns on other firms within the same industry contain important information for the determination of a given firm's underlying value but are unlikely to be affected by the expected bond liquidity of that firm. We run the same reduced form specification above, using industry, rather than firm, cumulative stock return. The results in Column 2 are similar to those in Column 1: cumulative industry returns have a significant negative effect on the bond's γ measure of illiquidity.

In the last three columns of Table 15, we estimate IV regressions via two-stage least squares (2SLS):

[38] We use the Fama-French 48 industries classification to assign firms to industries in constructing the portfolios.

$$Illiquidity_{i,t} = \alpha + \beta_1 \times Price_{i,t-1} + \beta_2 \times \mathbf{X}_{i,t-1} + \boldsymbol{\delta_t} + \boldsymbol{\theta_i} + \epsilon_{i,t} \tag{11}$$

and

$$Price_{i,t-1} = \delta + \eta_1 \times Z_{i,t-1} + \eta_2 \times \mathbf{X}_{i,t-1} + \boldsymbol{\tau_t} + \boldsymbol{\kappa_i} + \nu_{i,t}. \tag{12}$$

Regression 12, with $Price_{i,t-1}$ as the dependent variable, is the first stage in the estimation, and it includes an instrument (Z) that is excluded from the illiquidity regression (11). Column 3 of Table 15 presents estimates of the second-stage regression (11) using the lagged cumulative return on the stock of the issuing firm, $Cret_{i,t-1}$, as the instrument. The model includes bond and year-by-month fixed effects. Column 4 of Table 15 presents estimates of (11) using the lagged cumulative return on an equal-weighted portfolio of all the stocks in the issuing firm's industry – $Industry\,Cret_{i,t-1}$ – with the same fixed-effects specifications as in Column 3.

The 2SLS estimates of the effect of the bond price on γ is -0.133 when using the firm's own stock return as an instrument (Column 3) and is -0.167 when using industry returns as an instrument (Column 4), respectively. Thus, the instruments uncover a negative relation between bond liquidity and bond prices, which are larger than those documented in Table 3. We obtain similar results using the two other measures of illiquidity, *Amihud* and *IRT*, which we omit here for brevity.

In the last column of Table 15 we employ the same 2SLS identification strategy using a variant of the industry return instrument used in Column 4 of the Table. In particular, for each bond-month in the sample we calculate the lagged cumulative return on an equal-weighted portfolio of stocks in the issuing firm's industry since the first date the bond is traded in TRACE, *using only financially strong firms within the industry.* Financially strong firms are calculated as those with a ratio of earnings before interest, tax, depreciation, and amortization (EBITDA) to interest expense in the top of their respective industry quartile. The strong-firm industry instrument is meant to alleviate concerns that variation in returns of financially weak firms could be driven, in part, by changes in expected market liquidity, due for example to increased informational frictions in such firms. Put differently, equity movements in strong firms are plausibly less likely driven by changes in expected future liquidity movements, and more likely driven by changes to "market fundamentals." As can be seen from the last column of Table 15, using the strong-firm industry cumulative return variable to instrument for bond prices, we find a negative and statistically significant relation between bond illiquidity and bond price.

4.2 Large drops in stock returns

The results presented in Table 15 are based on firm- or industry-level cumulative stock returns. We supplement the cumulative returns analysis in Table 15 with IV regressions that are based on *large* lagged monthly stock returns as an instrument. For every bond-month in our sample we calculate the one-month lagged return on the stock of the issuing firm. We then define two dummy variables that equal one if the return on the stock in the previous month is less or equal to the 10th or 25th percentile, respectively, of the stock's return distribution during our sample period. Table 16 presents the summary statistics of lagged monthly stock returns that are at or below the 25th percentile (first row), above the 25th percentile (second row), at or below the 10th percentile (third row), and above the 10th percentile (fourth row). The 10th and 25th percentile-based dummies capture significant declines in one-month lagged stock returns with mean monthly returns of -0.145 and -0.099, respectively. These lagged large movements in stock returns are unlikely to be driven by anticipation of declining liquidity of the bonds issued by the same firm, and thus these large stock price declines dummies are valid instruments for $Price_{i,t-1}$ in equation 12. We report the results of the second-stage regression (11) using large stock price declines dummies as the instruments in Table 17. The first two columns of the table use the 25th percentile dummy as the instrument, while Columns 3 and 4 are estimated with the 10th percentile instrument. As Table 17 shows, and consistent with the findings in Tables 3, 4, and 15, large declines in stock prices are associated with shrinking liquidity of the bonds issued by the same firms.

4.3 Oil Prices

As our final empirical identification strategy, we estimate the effect of oil price shocks on the liquidity of bonds issued by oil and gas firms. We restrict our issuing firms to seven industries: Crude Petroleum and Natural Gas (SIC code 1311), Drilling Oil and Gas Wells (SIC code 1381), Oil and Gas Field Exploration Services (SIC codes 1382 and 1389), Petroleum Refining (2911), Miscellaneous Products of Petroleum and Coal (SIC code 2990), and Oil and Gas Field Machinery and Equipment (SIC code 3533). We also extend our sample period up to 2015 to cover the large decline in oil prices in 2014 and 2015. Oil prices directly affect the prices of oil and gas bonds, which in 2015 accounted for about 15 percent of high-yield bonds in the US bond market. The final sample size of oil and gas bonds for which we are able to calculate illiquidity measures ranges from 19,142 to 29,452 bond-year observations depending on the measure of illiquidity we use in the analysis. We present reduced form estimates of the effect of monthly oil prices on all three measures of illiquidity in Table 18.[39]

In Columns 1, 3, and 5 we regress each of the three measures of bond illiquidity on the natural log of monthly oil prices as well as bond and year fixed effects. As the table demonstrates, oil prices have a negative effect on illiquidity: higher oil prices make bonds more liquid. Although we cannot include year-by-month fixed effects, given that the underlying variation in oil prices is at the same level, the results are robust to the inclusion of bond and year fixed effects. We next add the issuing firm lagged leverage ratio and an interaction term between lagged leverage and log oil price. Oil and gas companies with higher financial leverage are more likely to be sensitive to oil prices as the exogenous price shock is amplified by their firm specific financial risk. As Columns 2, 4 and 6 demonstrate, that is exactly the case. Bonds of firms with higher leverage are less liquid and as the negative and significant coefficient on the interaction term shows – leverage amplifies the effect of oil prices on bond illiquidity.

5 Conclusion

We test several predictions of asymmetric-information-based models of bond liquidity. We show that bond illiquidity rises as bond price declines using both OLS and IV regression models. We conduct a series of empirical cross-sectional tests that pertain to predictions stemming from the asymmetric-information theory of bond liquidity of Dang et al. (2012). Our results are consistent with the model. Bond liquidity is determined by the informational sensitivity structure of debt contracts. When debt is deep in the money it becomes informationally insensitive; regardless of the realization of underlying firm value, the market value of debt will be very close to its face value. Even if parties may enjoy an informational advantage regarding underlying *firm* value, this informational advantage will not translate into asymmetric information regarding *debt* value: liquidity in this informationally insensitive region is predicted to be high. Our results shed new empirical light on the informational nature of "safe assets" and the determinants of their informational sensitivity and liquidity.

[39]For monthly oil prices we use the end-of-the month price per barrel of Europe Brent Spot Price FOB.

References

Acharya, Viral V., and Lasse H. Pedersen, “Asset Pricing with Liquidity Risk,” *Journal of Financial Economics* (2005), 77: 375-410.

Akerlof, George A., “The Market for “Lemons”: Quality Uncertainty and the Market Mechanism,” *Quarterly Journal of Economics* (1970), 488-500.

Aiyagari, S.R., and Mark Gertler, “Asset Returns with Transaction Costs and Uninsured Individual Risk,” *Journal of Monetary Economics* (1991), 27: 311-331.

Amihud, Yakov, “Illiquidity and Stock Returns: Cross-Section and Time-Series Effects,” *Journal of Financial Markets* (2002), 5: 31-56.

Amihud, Yakov, and Haim Mendelson, “Asset Pricing and the Bid-Ask Spread,” *Journal of Financial Economics* (1986), 17: 223-249.

Amihud, Yakov, and Haim Mendelson, “Liquidity, Maturity, and the Yields on U.S. Treasury Securities,” *Journal of Finance* (1991), 46: 1411-1425.

Bansal, Ravi., and John Coleman, “A Monetary Explanation of the Equity Premium, Term Premium, and the Risk-Free Rate Puzzles,” *Journal of Political Economy* (1996), Vol. 104 1135-1171.

Bao, Jack, Jun Pan, and Jian Wang, “Liquidity of Corporate Bonds,” *Journal of Finance* (2011), 66: 911-946.

Bao, Jack, Jia Chen, Kewei Hou, and Lei Lu, “Prices and Volatilities in the Corporate Bond Market,” *Working paper* (2015).

Bao, Jack and Kewei Hou, “De Facto Seniority, Credit Risk, and Corporate Bond Prices” *Review of Financial Studies* (2017), 30: 4038-4080.

Benmelech, Efraim and Nittai Bergman, “Credit Market Freezes,” *Working paper* (2018).

Brunnermeier, Markus K., and Lasse H., Pedersen, “Market Liquidity and Funding Liquidity,” *Review of Financial Studies* (2009), 22: 2201-2238.

Campbell, John, Jens Hilscher and Jan Szilagyi, “In Search of Distress Risk,” *Journal of Finance* (2008), 63: 2899-2939.

Carlson Mark, Burcu Duygan-Bump, Fabio Natalucci, Bill Nelson, Marcelo Ochoa, Jeremy C. Stein, and Skander Van den Heuvel, “The Demand for Short-Term, Safe Assets and Financial Stability: Some Evidence and Implications for Central Bank Policy,” *Working paper, Harvard*

University (2016).

Chen, Long, David A., Lesmond, and Jason Wei, "Corporate Yield Spreads and Bond Liquidity," *Journal of Finance* (2007), 62: 119-149.

Covitz, Dan, and Chris Downing, "Liquidity or Credit Risk? The Determinants of Very Short?Term Corporate Yield Spreads," *Journal of Finance* (2007), 62: 2303-2328.

Dang Tri Vi, Gary Gorton, and Bengt Holmström, "Ignorance, Debt and Financial Crises," *Working paper* (2012).

Dang Tri Vi, Gary Gorton, and Bengt Holmström, "The Information Sensitivity of a Security," *Working paper* (2013).

de Jong, Frank, and Joost Driessen, "Liquidity Risk Premia in Corporate Bond Markets," *Quarterly Journal of Finance,* (2012), 2.

Dick-Nielsen, Jens, Peter Feldhütter, and David Lando, "Corporate Bond Liquidity Before and After the Onset of the Subprime Crisis," *Journal of Financial Economics* (2012), 103: 471-492.

Feldhütter, Peter, "The Same Bond at Different Prices: Identifying Search Frictions and Selling Pressures," *Review of Financial Studies* (2012), 25: 1155-1206.

Friewald, Nils , Christopher A. Hennessy and Rainer Jankowitsch, "Secondary Market Liquidity and Security Design: Theory and Evidence from ABS Markets," *Review of Financial Studies* (2016), 29: 1254-1290.

Garleanu, Nicolae B., and and Lasse H., Pedersen, 'Liquidity and Risk Management," *American Economic Review Papers and Proceedings,* (2007), 97: 193-197.

Goldstein, Michael A., Edith S. Hotchkiss and Erik R. Sirri, "Transparency and Liquidity: A Controlled Experiment on Corporate Bonds," *Review of Financial Studies* (2007), 20: 253-273.

Gorton, Gary B.,"Slapped by the Invisible Hand: The Panic of 2007," *Oxford University Press* (2010).

Gorton, Gary B.,"The History and Economics of Safe Assets," *NBER Working Paper* (2016).

Gorton, Gary B., and Andrew Metrick, "Securitized Banking and the Run on Repo," *Journal of Financial Economics* (2012), 103: 425-451.

Gorton, Gary B., and George Pennacchi, "Financial Intermediaries and Liquidity Creation," *Journal of Finance* (1990), 45: 49-72.

Greenwood, Robin, Samuel G. Hanson, and Jeremy C. Stein, "A Comparative-Advantage Approach to Government Debt Maturity," *Journal of Finance* (2015), 70: 1683-1722.

Grossman, S J., and M. H. Miller, "Liquidity and Market Structure," *Journal of Finance* (1988), 43: 617-633.

Hameed, Allaudeen, Wenjin Kang and S. Viswanathan, "Stock Market Declines and Liquidity," *Journal of Finance* (2010), 65: 257-293.

Hanson, Samuel G., and Adi Sunderam., "Are There Too Many Safe Securities? Securitization and the Incentives for Information Production," *Journal of Financial Economics* (2013), 108: 565-584.

Harris, Milton, and Artur Raviv, "Differences of Opinions Make a Horse Race," *Review of Financial Studies* (1993), 6: 473-506.

He, Zhighu, and Konstantin Milbradt, "Endogenous Liquidity and Defaultable Bonds,," *Econometrica* (2014), 84: 1443-1508.

Heaton, John, and Deborah Lucas., "Evaluating the Effects of Incomplete Markets on Risk Sharing and Asset Pricing," *Journal of Political Economics* (1996), 104: 443-487.

Holmström, Bengt, "Understanding the Role of Debt in the Financial System," *BIS working paper* (2015).

Krishnamurthy, Arvind, and Annette Vissing-Jorgensen, "The Aggregate Demand for Treasury Debt," *Journal of Political Economy* (2012), 120: 233-567.

Kwan, Simon, "Firm-specific Information and the Correlation between Individual Stocks and Bonds," *Journal of Financial Economics* (1996), 40: 63-80.

Lando, David, and Torben M. Skødeberg, "Analyzing Rating Transitions and Rating Drift with Continuous Observations," *Journal of Banking and Finance* (2002), 26: 423-444.

Longstaff, Francis A., "The Flight-to-Liquidity Premium in U.S. Treasury Bond Prices," *Journal of Business* (2004), 77: 511-526.

Myers, Stewart C., and Nicholas S., Majluf, "Corporate Financing and Investment Decisions when Firms Have Information That Investors Do Not Have," *Journal of Financial Economics* (1984) 13: 187-221.

Pastor, Lubos, and Robert F. Stambaugh., "Liquidity Risk and Expected Stock Returns," *Journal of Political Economy* (2003), 111: 642-685.

Rocheteau, Guillaume, "A Monetary Approach to Asset Liquidity," Working Paper, University of California-Irvine, 2010.

Sadka, Ronnie, "Momentum and Post-Earnings-Announcement Drift Anomalies: The Role of Liquidity Risk," *Journal of Financial Economics* (2006), 80: 309-349.

Spence, Michael, "Job Market Signaling," *Quarterly Journal of Economics* (1973), 355-374.

Stein, Jeremy C., "Monetary Policy as Financial Stability Regulator," *Quarterly Journal of Economics* (2012), 57-95.

Stoll, H. R., "The Supply of Dealer Services in Securities Markets," *Journal of Finance* (1978), 33: 1133-51.

Sunderam, Adi, "Money Creation and the Shadow Banking System," *Review of Financial Studies* (2015) 28: 939-977.

Varian, H. R., "Differences of Opinion in Financial Markets," in Courtenay C. Stone (ed.), Financial Risk: Theory, Evidence and Implications, Kluwer, Boston, (1989) 3-37.

Vayanos, Dimitri, "Flight to Quality, Flight to Liquidity, and the Pricing of Risk," *Working Paper, London School of Economics* (2004).

Vayanos, Dimitri, and Jean-Luc Vila, "Equilibrium Interest Rates and Liquidity Premium With Transaction Costs," *Economic Theory* (1999), 509-539.

Vissing-Jorgensen, Annette, "Perspectives on Behavioral Finance: Does 'Irrationality' Disappear with Wealth? Evidence from Expectations and Actions," *NBER Macroeconomics Annual* (2003) 18:139-208.

Weill, Pierre-Olivier, "Leaning Against the Wind," *Review of Economic Studies* (2007) 74:1329-54.

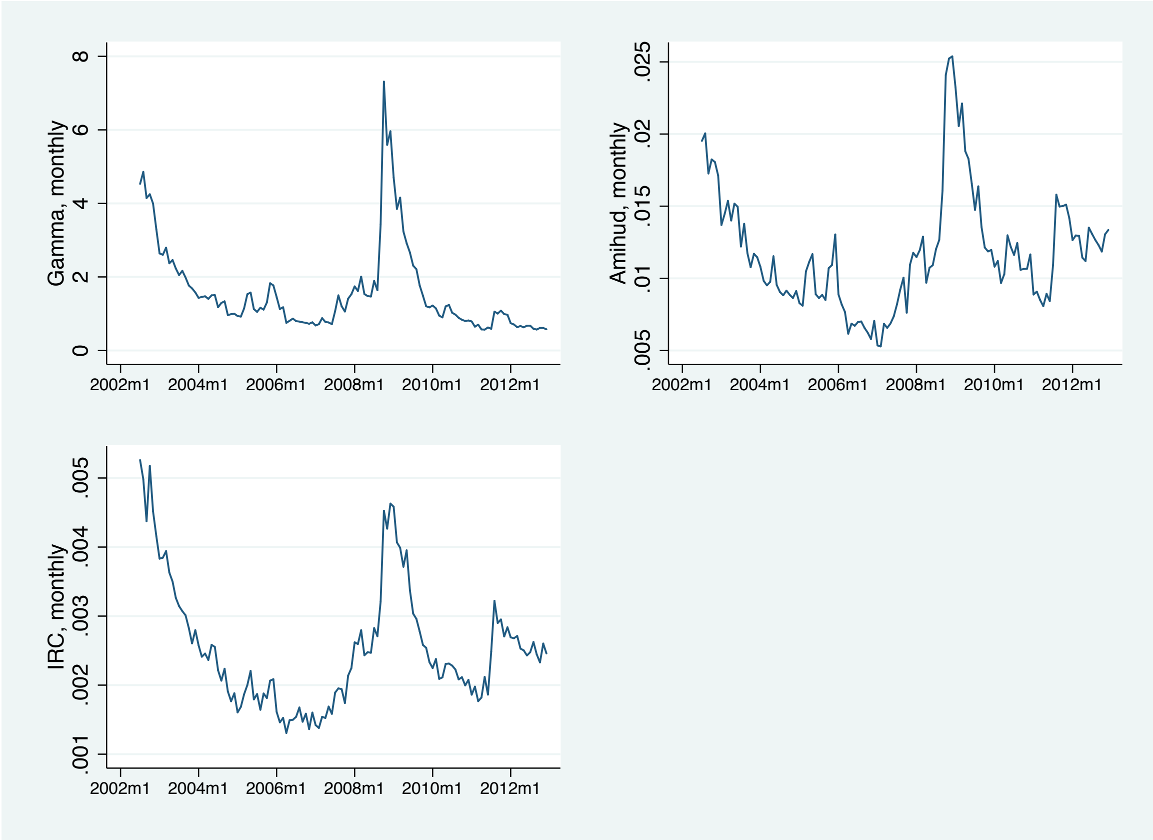

Figure 1: Liquidity over Time, Cross-sectional Means

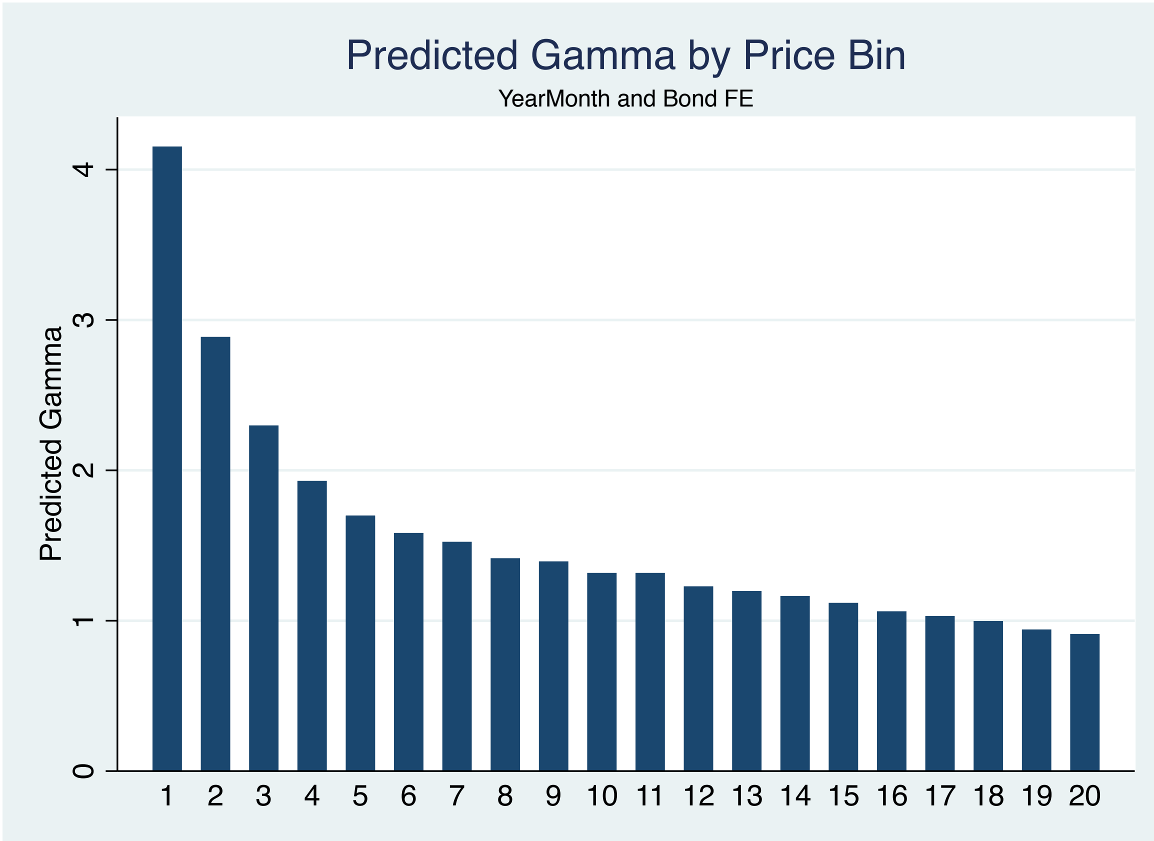

Figure 2: Liquidity and Bond Prices

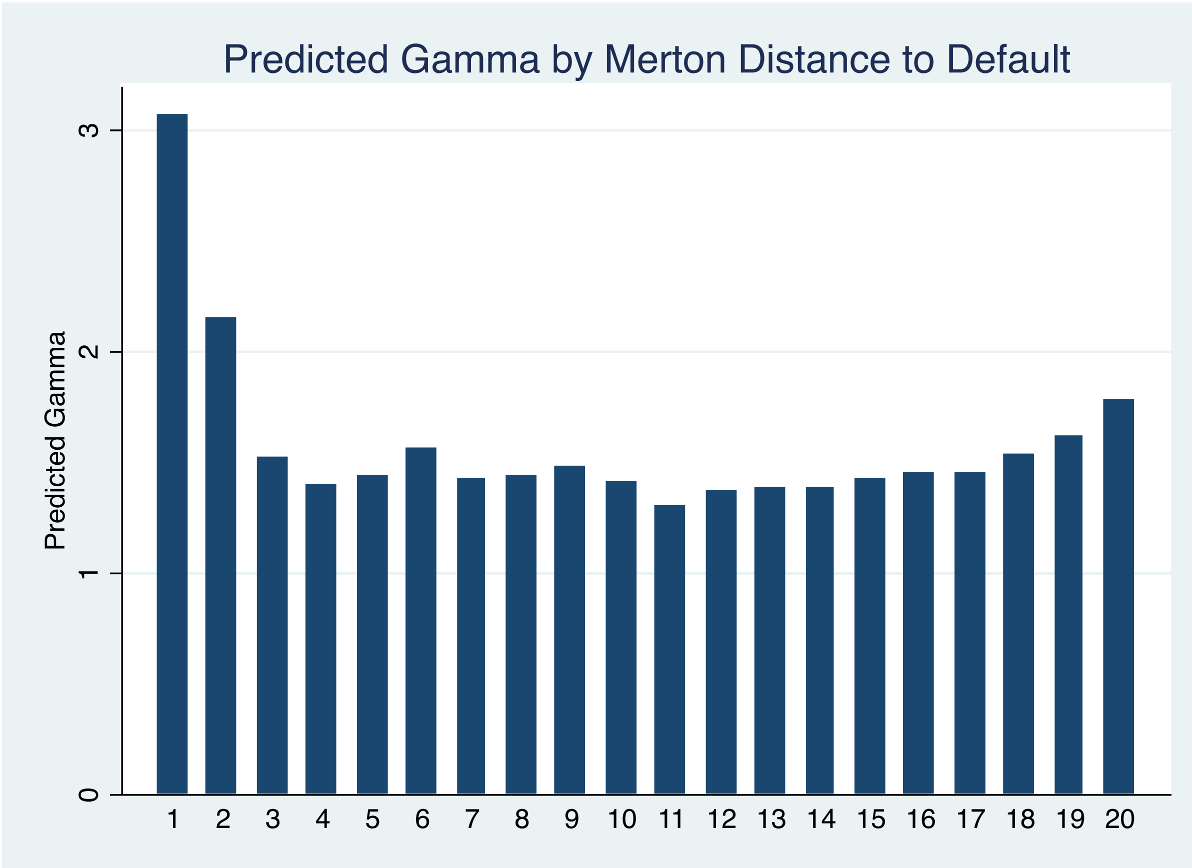

Figure 3: Liquidity and Merton Distance-to-Default

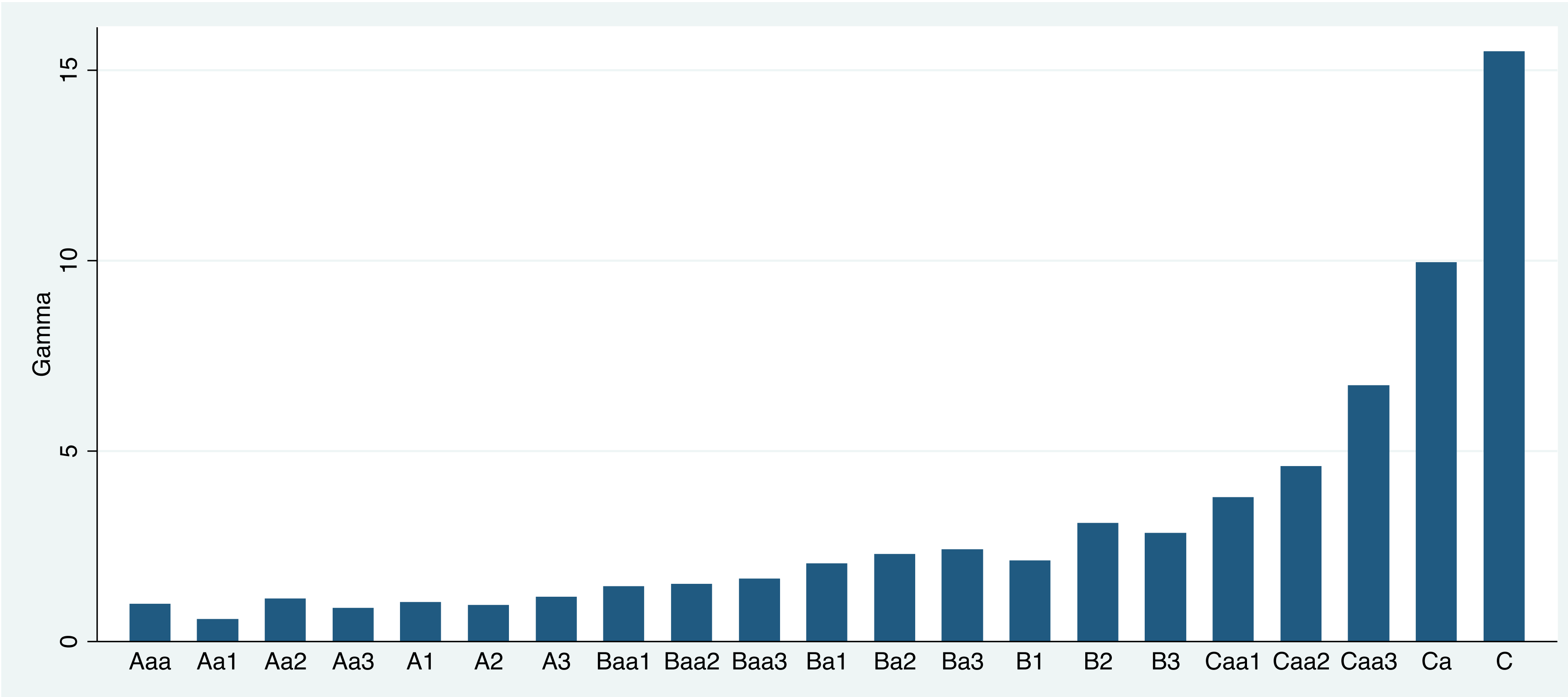

Figure 4: Liquidity and Credit Rating

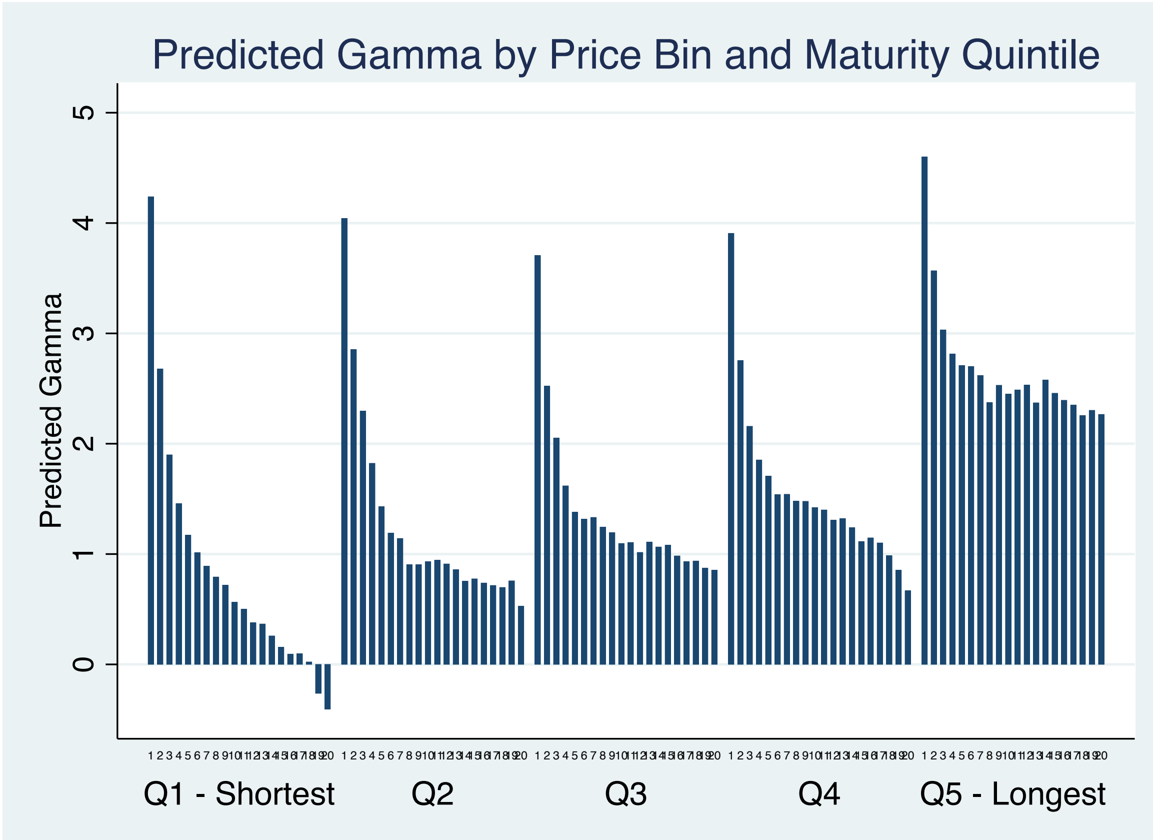

Figure 5: Liquidity by Price Bin and Maturity Quintile

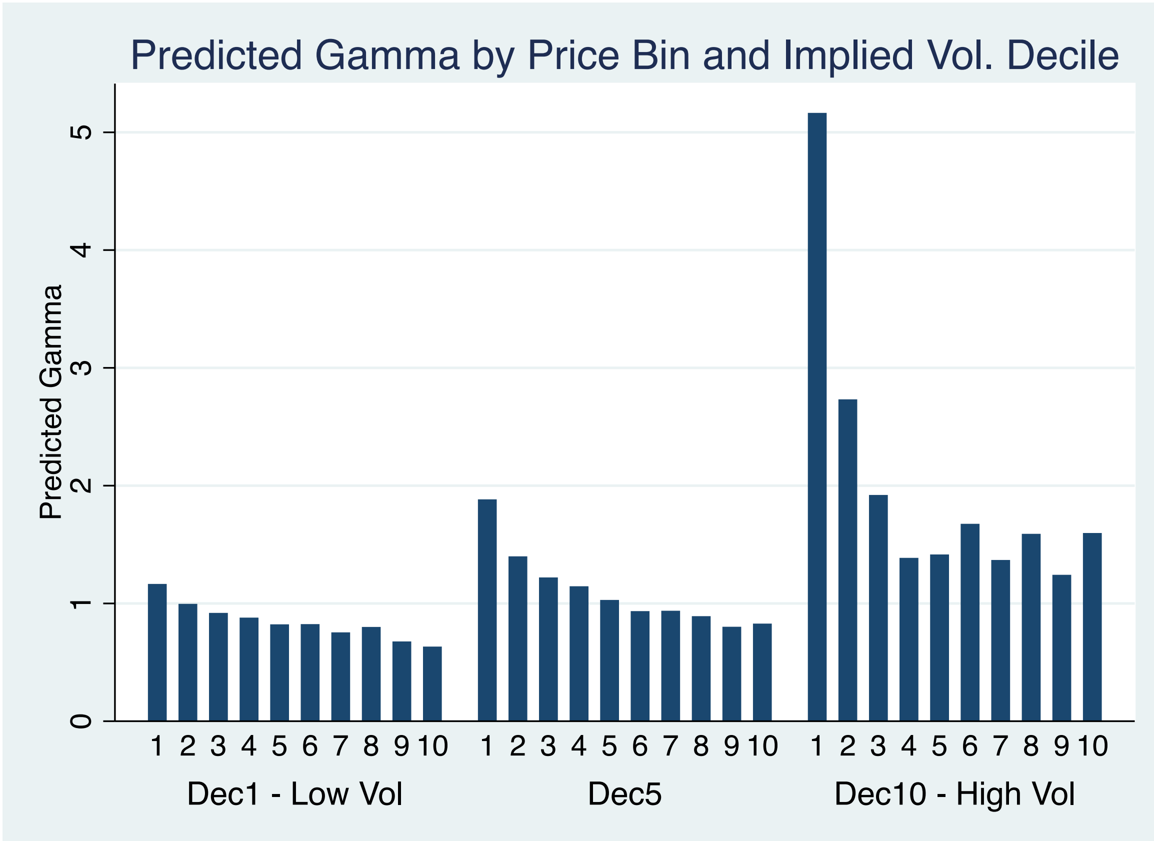

Figure 6: Liquidity by Price Bin and Implied Volatility

Table 1: Bond Characteristics

	Mean	Standard Deviation	25th Percentile	Median	75th Percentile	Observations
Gamma	1.533	3.145	0.136	0.484	1.460	178,971
Amihud	0.0119	0.0189	0.00159	0.00478	0.0131	245,633
IRT	0.00256	0.00353	0.000401	0.00134	0.00321	248,920
Price	104.0	11.82	99.06	103.5	109.2	465,719
Time to Maturity	8.675	9.907	2.542	5.042	9.625	465,719
Yield Spread	0.0238	0.0619	0.00897	0.0151	0.0258	465,637
Moody's Rating	Baa1	-	Baa3	Baa31	A2	465,719
Amount Outstanding	367,402	469,414	67,000	250,000	500,000	465,662

This table provides summary statistics for bond characteristics.

Table 2: The Evolution of Bond Illiquidity over Time

	Mean	Standard Deviation	25th Percentile	Median	75th Percentile	Observations
			Panel A: 2002-6			
Gamma	1.739	3.438	0.147	0.549	1.692	70,870
Amihud	0.0110	0.0191	0.00114	0.00364	0.0114	106,580
IRT	0.00257	0.00389	0.000254	0.00114	0.00307	104,821
			Panel B: 2007-9			
Gamma	2.270	4.063	0.254	0.797	2.242	43,253
Amihud	0.0136	0.0205	0.00175	0.00577	0.0159	63,886
IRT	0.00280	0.00360	0.000484	0.00166	0.00361	64,148
			Panel C: 2010-12			
Gamma	0.815	1.561	0.0885	0.308	0.880	64,848
Amihud	0.0116	0.0171	0.00237	0.00558	0.0131	75,167
IRT	0.00236	0.00290	0.000534	0.00141	0.00305	79,951

This table presents the evolution of our three measures of bond Illiquidity over time. The table provides summary statistics for the three liquidity measures for three subperiods: 2002-6 (Panel A), 2007-9 (Panel B) and 2010-12 (Panel C).

Table 3: Bond Illiquidity (Gamma) and Bond Price

	(1) Gamma	(2) Gamma	(3) Gamma	(4) Gamma	(5) Gamma	(6) Gamma	(7) Gamma	(8) Gamma	(9) Gamma	(10) Gamma	(11) Gamma	(12) Gamma
Spread_{t-1}	19.529 ***	17.724 ***	17.332 ***	14.663 ***	17.204 ***	14.091 ***						
	(2.499)	(2.251)	(2.714)	(2.357)	(2.491)	(2.105)						
Price_{t-1}							-0.097 ***	-0.090 ***	-0.093 ***	-0.082 ***	-0.126 ***	-0.112 ***
							(0.011)	(0.012)	(0.006)	(0.006)	(0.003)	(0.003)
Constant	3.111 ***	1.103 ***	3.068 ***	1.211 ***	3.614 ***	1.197 ***	13.564 ***	10.564 ***	12.927 ***	9.737 ***	16.511 ***	12.673 ***
	(0.351)	(0.094)	(0.192)	(0.094)	(0.137)	(0.085)	(1.103)	(1.173)	(0.653)	(0.659)	(0.350)	(0.351)
Adjusted R^2	0.21	0.25	0.29	0.32	0.35	0.39	0.23	0.27	0.30	0.33	0.39	0.41
Observations	176,316	176,316	176,316	176,316	176,316	176,316	176,328	176,328	176,328	176,328	176,328	176,328
Bond Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects												
industry	Yes	Yes	No	No	No	No	Yes	Yes	No	No	No	No
firm	No	No	Yes	Yes	No	No	No	No	Yes	Yes	No	No
bond	No	No	No	No	Yes	Yes	No	No	No	No	Yes	Yes
year	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
year × month	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

This table reports the coefficients and standard errors from a regression of the Gamma measure of bond illiquidity on either the lagged credit spread (Columns 1-6) or lagged bond price (Columns 7-12), as well as a vector of bond characteristics that includes the issue size and time since issuance. Depending on the specification, we include industry, firm, bond, year. and year-by-month fixed effects. Robust standard errors in parentheses are clustered by bond: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Bond Illiquidity (Amihud) and Bond Price

	Amihud	Amihud	Amihud	Amihud	Amihud	Amihudq	Amihud	Amihud	Amihud	Amihud	Amihud	Amihud
Spread_{t-1}	0.040 ***	0.035 ***	0.036 ***	0.029 ***	0.034 ***	0.025 ***						
	(0.007)	(0.006)	(0.008)	(0.007)	(0.007)	(0.005)						
Price_{t-1}							-0.0002 ***	-0.0002 ***	-0.0002 ***	-0.00002 ***	-0.0002 ***	-0.0002***
							(0.00005)	(0.0005)	(0.00002)	(0.00002)	(0.00001)	(0.00001)
Constant	0.016 ***	0.011 ***	0.015 ***	0.009 ***	0.016 ***	0.009 ***	0.041 ***	0.030 ***	0.036 ***	0.024 ***	0.041 ***	0.027 ***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.0004)	(0.001)	(0.005)	(0.004)	(0.002)	(0.002)	(0.001)	(0.002)
Adjusted R^2	0.11	0.12	0.19	0.21	0.26	0.28	0.11	0.12	0.19	0.21	0.26	0.28
Observations	233,881	233,881	233,881	233,881	233,881	233,881	233,904	233,904	233,904	233,904	233,904	233,904
Bond Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects												
industry	Yes	Yes	No	No	No	No	Yes	Yes	No	No	No	No
firm	No	No	Yes	Yes	No	No	No	No	Yes	Yes	No	No
bond	No	No	No	No	Yes	Yes	No	No	No	No	Yes	Yes
year	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
year × month	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

This Table reports the coefficients and standard errors from a regression of the Amihud measure of bond illiquidity on either the lagged credit spread (Columns 1-6) or lagged bond price (Columns 7-12), as well as a vector of bond characteristics that includes the issue size and time since issuance. Depending on the specification, we include industry, firm, bond, year, and year-by-month fixed effects. Robust standard errors in parentheses are clustered by bond: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Correlation Matrix: Bond Illiquidity and Volatility

	Gamma	Amihud	IRT	Implied Volatility	Bond Volatility
Gamma	1.000				
Amihud	0.328	1.000			
IRT	0.341	0.510	1.000		
Implied Volatility	0.293	0.157	0.245	1.000	
Bond Volatility	0.026	0.019	0.015	0.019	1.000

This table reports Pearson product-moment correlation coefficients between each of the three measures of bond illiquidity, implied volatility, and bond volatility.

Table 6: Robustness Tests: Volatility, Non-Crisis Years and Investment Grade

Period	2002-12	2002-12	2002-12	2002-12	2002-12	2002-12	Excl. 2008-09	2008-2009	2002-12	2002-12
Rating	All	All	All	All	All	All	All	All	Investment Grade	Non-Investment Grade
Lagged Price	-0.0785***	-0.0687 ***	-0.081 ***	-0.0671 ***	-0.123 ***	-0.105 ***	-0.077 ***	-0.172 ***	-0.096 ***	-0.128 ***
	(0.012)	(0.012)	(0.011)	(0.011)	(0.010)	(0.011)	(0.004)	(0.007)	(0.004)	(0.005)
Lagged Implied Volatility	1.349 ***	1.373 ***	1.028 ***	0.904 ***	0.259	0.223				
	(0.294)	(0.285)	(0.222)	(0.189)	(0.191)	(0.152)				
Lagged Bond Volatility	0.008	0.007	0.006	0.005	0.004	0.003				
	(0.006)	(0.005)	(0.005)	(0.004)	(0.003)	(0.002)				
Adjusted R^2	0.218	0.2663	0.283	0.332	0.376	0.419	0.408	-.460	0.378	0.460
Observations	148,679	148,679	148,679	148,679	148,679	148,679	145,086	31,236	143,601	31.666
Bond Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Fixed Effects										
industry	Yes	Yes	No	No	No	No	No	No	No	No
firm	No	No	Yes	Yes	No	No	No	No	No	No
bond	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	No	Yes	No	Yes	No	No	No	No	No
year × month	No	Yes	No	Yes	No	Yes	Yes	Yes	Yes	Yes

This table reports the coefficients and standard errors from a regression of the Gamma measure of bond illiquidity on lagged bond price, lagged implied volatility and lagged bond volatility, as well as a vector of bond characteristics that includes the issue size and time since issuance. Depending on the specification, we include industry, firm, bond, year, and year-by-month fixed effects. Robust standard errors in parentheses are clustered by bond: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Price Deciles and Bond Illiquidity

	Gamma	Gamma	Amihud/100	Amihud/100	IRT/100	IRT/100
Price Deciles$_{t-1}$						
2.	-1.356 ***	-1.289 ***	-0.31 ***	-0.27 ***	-0.1 ***	-0.093 ***
	(0.07)	(0.067)	(0.027)	(0.027)	(5.07e-03)	(5.03e-03)
3.	-1.936 ***	-1.762 ***	-0.45 ***	-0.38 ***	-0.122 ***	-0.114 ***
	(0.0752)	(0.07)	(0.029)	(0.029)	(5.38e-03)	(5.38e-03)
4.	-2.169 ***	-1.93 ***	-0.51 ***	-0.41 ***	-0.139 ***	-0.127 ***
	(0.077)	(0.072)	(0.029)	(0.029)	(5.33e-03)	(5.36e-03)
5.	-2.367 ***	-2.046 ***	-0.57 ***	-0.45 ***	-0.155 ***	-0.139 ***
	(0.078)	(0.073)	(0.03)	(0.03)	(5.39e-03)	(5.44e-03)
6.	-2.518 ***	-2.126 ***	-0.62 ***	-0.47 ***	-0.162 ***	-0.143 ***
	(0.078)	(0.074)	(0.031)	(0.031)	(5.43e-03)	(5.53e-03)
7.	-2.674 ***	-2.217 ***	-0.68 ***	-0.51 ***	-0.173 ***	-0.152 ***
	(0.08)	(0.076)	(0.031)	(0.032)	(5.54e-03)	(5.70e-03)
8.	-2.812 ***	-2.305 ***	-0.69 ***	-0.51 ***	-0.175 ***	-0.153 ***
	(0.082)	(0.079)	(0.032)	(0.034)	(5.65e-03)	(5.89e-03)
9.	-2.954 ***	-2.376 ***	-0.69 ***	-0.49 ***	-0.185 ***	-0.162 ***
	(0.084)	(0.082)	(0.033)	(0.036)	(5.83e-03)	(6.21e-03)
10.	-3.108 ***	-2.455 ***	-0.71 ***	-0.48 ***	-0.199 ***	-0.174 ***
	(0.093)	(0.093)	(0.039)	(0.042)	(6.87e-03)	(7.41e-03)
Adjusted R^2	0.37	0.41	0.29	0.31	0.26	0.27
Observations	176,328	176,328	233,904	233,904	235,650	235,650
Bond Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects						
bond	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	No	Yes	No	Yes	No
year × month	No	Yes	No	Yes	No	Yes

This table reports the coefficients and standard errors from a regression of the three measures of bond illiquidity on 10 indicator variables that are based on bond price deciles, as well as a vector of bond characteristics that includes the issue size and time since issuance. Depending on the specification, we include bond, year, and year-by-month fixed effects. Robust standard errors in parentheses are clustered by bond: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Credit Rating and Bond Illiquidity

	Gamma	Gamma	Gamma	Gamma	Gamma	Gamma
Credit Rating Bins_{t-1}						
2.	0.194	0.192	0.113	0.108	-0.036	-0.036
	(0.165)	(0.168)	(0.091)	(0.097)	(0.068)	(0.071)
3.	0.808 ***	0.804 ***	0.616 ***	0.590 ***	0.235 ***	0.211 **
	(0.210)	(0.211)	(0.143)	(0.146)	(0.088)	(0.091)
4.	1.347 ***	1.358 ***	0.944 ***	0.938 ***	0.403 ***	0.404 ***
	(0.259)	(0.251)	(0.239)	(0.222)	(0.118)	(0.120)
5.	1.597 ***	1.600 ***	1.187 ***	1.168 ***	0.562 ***	0.552 ***
	(0.341)	(0.338)	(0.264)	(0.256)	(0.168)	(0.169)
6.	2.969 ***	3.025 ***	1.661 ***	1.717 ***	0.972 ***	1.005 ***
	(0.338)	(0.346)	(0.418)	(0.412)	(0.247)	(0.235)
7.	7.629 ***	7.482 ***	6.037 ***	5.797 ***	5.333 ***	5.080 ***
	(2.004)	(1.878)	(1.628)	(1.457)	(0.825)	(0.765)
Adjusted R^2	0.17	0.22	0.24	0.30	0.32	0.37
Observations	176,328	176,328	176,328	176,328	176,328	176,328
Bond Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects						
industry	Yes	Yes	No	No	No	No
firm	No	No	Yes	Yes	No	No
bond	No	No	No	No	Yes	Yes
year	Yes	No	Yes	No	Yes	No
year × month	No	Yes	No	Yes	No	Yes

This table reports the coefficients and standard errors from a regression of Gamma measure of bond illiquidity on seven indicator variables that are based on bond Moody's credit ratings, where Category 1 corresponds to the highest ratings and Category 7 corresponds to the lowest ratings, as well as a vector of bond characteristics that includes the issue size and time since issuance. Depending on the specification, we include industry, firm, bond, year, and year-by-month fixed effects. Robust standard errors in parentheses are clustered by bond: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Information Infrastructure and Bond Illiquidity

Dependent Variable	Gamma	Gamma	Gamma	Gamma	Gamma	Gamma
ΔCredit Rating	0.237 ***	0.106 ***	0.122***	0.302 ***	0.131 ***	0.146 ***
	(0.044)	(0.035)	(0.033)	(0.048)	(0.039)	(0.038)
Months Elapsed since previous rating				0.006 ***	0.007 ***	0.004 **
				(0.002)	(0.002)	(0.002)
Months Elapsed since previous rating				-0.007 **	-0.004 ***	-0.003 ***
×ΔCredit Rating				(0.001)	(0.001)	(0.001)
Price_{t-1}		-0.131 ***	-0.126 ***		-0.131 ***	-0.126 ***
		(0.006)	(0.007)		(0.006)	(0.007)
Lagged Implied Volatility			-0.105			-0.106
			(0.257)			(0.260)
Lagged Bond Volatility			0.009			0.009
			(0.007)			(0.007)
Adjusted R^2	0.41	0.46	0.46	0.41	0.46	0.46
Observations	52,714	52,216	43,373	52,714	52,216	43,373
Bond Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects						
bond	Yes	Yes	Yes	Yes	Yes	Yes
current credit rating	Yes	Yes	Yes	Yes	Yes	Yes
year × month	Yes	Yes	Yes	Yes	Yes	Yes

This table reports the coefficients and standard errors from a regression of Gamma measure of bond illiquidity on ΔCredit Rating – the bond-level difference between the previous and the current credit rating, the time (in months) that elapsed since the previous rating action, the interaction between ΔCredit Rating and the time that elapsed since the last credit rating action, as well as seven indicator variables that are based on bond Moody's credit ratings, where Category 1 corresponds to the highest ratings and Category 7 corresponds to the lowest ratings, lagged bond price, lagged implied volatility, lagged bond volatility, and a vector of bond characteristics that includes the issue size and time since issuance. All specifications include bond and year-by-month fixed effects. Robust standard errors in parentheses are clustered by bond: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 10: Analysts Coverage and Bond Illiquidity

	Gamma	Gamma
Lagged Price	-0.147 ***	-0.130 ***
	(0.008)	(0.008)
Analysts Coverage Quintiles$_{t-1}$		
2.	1.683 **	1.647 *
	(0.859)	(0.847)
3.	-2.400 ***	-1.805 **
	(0.895)	(0.877)
4.	-4.600 ***	-3.886 ***
	(0.902)	(0.875)
5.	-5.857 **	-5.221 ***
	(1.194)	(1.184)
Lagged Price		
× Analysts Coverage Quintile 2	-0.015 *	-0.015 *
	(0.008)	(0.008)
× Analysts Coverage Quintile 3	0.023 ***	0.018 **
	(0.009)	(0.008)
× Analysts Coverage Quintile 4	0.044 ***	0.038 **
	(0.009)	(0.008)
× Analysts Coverage Quintile 5	0.055 ***	0.050 ***
	(0.011)	(0.022)
Adjusted R^2	0.41	0.45
Observations	92.022	92.022
Bond Characteristics	Yes	Yes
Fixed Effects		
bond	Yes	Yes
year	Yes	No
year × month	No	Yes

This table reports the coefficients and standard errors from a regression of Gamma measure of bond illiquidity on lagged bond price, indicators variables defined from five quintiles of analysts coverage, as well as the interactions between the analysts coverage quintiles and lagged price, and a vector of bond characteristics that includes the issue size and time since issuance. Specifications include bond and either year, or year-by-month fixed effects. Robust standard errors in parentheses are clustered by bond: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 11: Collateral and Bond Illiquidity

	Gamma	Amihud	IRT
Secured Bond	-0.895 ***	-0.005 *	-0.002 ***
	(0.339)	(0.002)	(0.0004)
Credit Rating Bins$_{t-1}$			
2.	0.255	0.003 *	0.0005 *
	(0.284)	(0.0019)	(0.0003)
3.	0.655 *	0.007 ***	0.0009 ***
	(0.376)	(0.002)	(0.0003)
4.	0.730	0.007 **	0.0012 ***
	(0.518)	(0.003)	(0.0004)
5.	1.522 **	0.008 ***	0.0013 ***
	(0.644)	(0.003)	(0.0005)
6.	2.326 ***	0.005	0.0010 *
	(0.646)	(0.004)	(0.0006)
7.	6.223 ***	0.017 ***	0.0015 *
	(1.086)	(0.005)	(0.001)
Adjusted R^2	0.35	0.21	0.18
Observations	13,194	19,766	20,474
Number of Issuers	201	278	282
Number of Bonds	460	670	681
Bond Characteristics	Yes	Yes	Yes
Fixed Effects			
firm	Yes	Yes	Yes
year	Yes	Yes	Yes

This table reports the coefficients and standard errors from a regression of three measures of bond illiquidity on a dummy variable that takes the value of one if the bond is secured, and zero otherwise, as well as seven indicator variables that are based on bond Moody's credit ratings, where Category 1 corresponds to the highest ratings and Category 7 corresponds to the lowest ratings, and a vector of bond characteristics that includes the issue size and time since issuance. Specifications include firm and year fixed effects. Robust standard errors in parentheses are clustered by bond: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 12: Maturity and Bond Illiquidity

	Gamma	Gamma	Gamma	Gamma	Gamma	Gamma
Maturity Quintile$_{t-1}$						
2.	0.417 ***	0.409 ***	0.420 ***	0.411 ***	0.178 ***	0.144 ***
	(0.091)	(0.092)	(0.057)	(0.059)	(0.040)	(0.041)
3.	0.673 ***	0.675 ***	0.636 ***	0.636 ***	0.287 ***	0.251 ***
	(0.099)	(0.105)	(0.053)	(0.055)	(0.063)	(0.065)
4.	0.928 ***	0.935 ***	0.942 ***	0.947 ***	0.455 ***	0.400 ***
	(0.123)	(0.128)	(0.058)	(0.059)	(0.096)	(0.099)
5.	2.220 ***	2.232 ***	2.029 ***	2.046 ***	1.549 ***	1.460 ***
	(0.208)	(0.214)	(0.087)	(0.089)	(0.273)	(0.271)
Adjusted R^2	0.19	0.24	0.27	0.32	0.31	0.37
Observations	176,328	176,328	176,328	176,328	176,328	176,328
Bond Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects						
industry	Yes	Yes	No	No	No	No
firm	No	No	Yes	Yes	No	No
bond	No	No	No	No	Yes	Yes
year	Yes	No	Yes	No	Yes	No
year × month	No	Yes	No	Yes	No	Yes

This table reports the coefficients and standard errors from a regression of the Gamma measure of bond illiquidity on a indicator variables defined from five equal-sized quintiles of bond maturity, and a vector of bond characteristics that includes the issue size and time since issuance. Specifications include industry, firm, bond, year, and year-by-month fixed effects. Robust standard errors in parentheses are clustered by bond: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 13: Price Deciles and Bond Illiquidity, by Maturity Quintiles

	Quintile 1 (Short)	Quintile 2	Quintile 3	Quintile 4	Quintile 5 (long)
Price Deciles$_{t-1}$					
2.	-1.333 ***	-1.129 ***	-1.043 ***	-1.164 ***	-1.156 ***
	(0.203)	(0.196)	(0.130)	(0.125)	(0.136)
3.	-1.843 ***	-1.859 ***	-1.532 ***	-1.536 ***	-1.374 ***
	(0.228)	(0.223)	(0.149)	(0.133)	(0.137)
4.	-2.069 ***	-2.121 ***	-1.586 ***	-1.642 ***	-1.573 ***
	(0.243)	(0.219)	(0.156)	(0.142)	(0.152)
5.	-2.238 ***	-2.216 ***	-1.726 ***	-1.699 ***	-1.594 ***
	(0.253)	(0.221)	(0.158)	(0.144)	(0.149)
6.	-2.414 ***	-2.205 ***	-1.808 ***	-1.790 ***	-1.566 ***
	(0.262)	(0.218)	(0.160)	(0.150)	(0.149)
7.	-2.511 ***	-2.305 ***	-1.775 ***	-1.858 ***	-1.598 ***
	(0.270)	(0.222)	(0.164)	(0.162)	(0.143)
8.	-2.681 ***	-2.341 ***	-1.819 ***	-2.000 ***	-1.654 ***
	(0.282)	(0.223)	(0.168)	(0.179)	(0.151)
9.	-2.717 ***	-2.371 ***	-1.903 ***	-2.072 ***	-1.780 ***
	(0.299)	(0.225)	(0.176)	(0.197)	(0.161)
10.	-3.013 ***	-2.323 ***	-1.960 ***	-2.281 ***	-1.785 ***
	(0.364)	(0.249)	(0.206)	(0.219)	(0.187)
Adjusted R^2	0.52	0.51	0.47	0.41	0.41
Observations	28,864	34,968	37,545	42,093	32,858
Bond Characteristics	Yes	Yes	Yes	Yes	Yes
Fixed Effects					
bond	Yes	Yes	Yes	Yes	Yes
year × month	Yes	Yes	Yes	Yes	Yes

This table reports the coefficients and standard errors from a regression of the Gamma measure of bond illiquidity on 10 indicator variables that are based on bond price deciles, as well as a vector of bond characteristics that includes the issue size and time since issuance. We run the regressions separately for each of the five maturity quintiles. Column 1 reports results for bonds in Quintile 1 (short) and Column 5 reports results for bonds in Quintile 5 (long). All specification include bond and year-by-month fixed effects. Robust standard errors in parentheses are clustered by bond: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 14: Bond Illiquidity, Price, and Equity Implied Volatility

	Gamma	Gamma	Gamma	Gamma
Implied Vol Quintiles$_{t-1}$				
2.	0.176	0.268	0.518	0.686*
	(0.475)	(0.470)	(0.368)	(0.364)
3.	1.157*	0.972	0.919*	0.721*
	(0.646)	(0.644)	(0.416)	(0.412)
4.	4.964***	4.024***	3.497***	2.333***
	(0.773)	(0.744)	(0.508)	(0.495)
5.	15.70***	13.41***	11.76***	9.089***
	(0.916)	(0.899)	(0.621)	(0.623)
Price$_{t-1}$	-0.01*	-0.01*	-0.054***	-0.054***
	(0.005)	(0.005)	(0.004)	(0.004)
Price$_{t-1}$				
× Implied Volatility Quintile 2.	-0.00132	0.00360	-0.00428	-0.00745**
	(0.00432)	(0.00430)	(0.00342)	(0.00338)
× Implied Volatility Quintile 3.	-0.0101*	-0.0110*	-0.00767**	-0.00895**
	(0.006)	(0.006)	(0.004)	(0.004)
× Implied Volatility Quintile 4.	-0.0440***	-0.0397***	-0.0305***	-0.0249***
	(0.007)	(0.007)	(0.005)	(0.005)
× Implied Volatility Quintile 5.	-0.145***	-0.131***	-0.108***	-0.0916***
	(0.009)	(0.009)	(0.006)	(0.006)
Adjusted R^2	0.36	0.39	0.44	0.47
Observations	92,898	92,898	92,898	92,898
Bond Characteristics	Yes	Yes	Yes	Yes
Fixed Effects				
firm	Yes	Yes	No	No
bond	No	No	Yes	Yes
year	Yes	No	Yes	No
year × month	No	Yes	No	Yes

This table reports the coefficients and standard errors from a regression of Gamma measure of bond illiquidity on lagged bond price, indicators variables defined from five quintiles of implied volatility, as well as the interactions between the implied volatility quintiles and lagged price and a vector of bond characteristics that includes the issue size and time since issuance. Specifications include firm, bond, and either year or year-by-month fixed effects. Robust standard errors in parentheses are clustered by bond: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 15: Instrumental Variables Regressions of Illiquidity on Bond Prices

	Gamma	Gamma	Gamma	Gamma	Gamma
Cumulative Stock Return	-0.281 ***				
	(0.035)				
Cumulative Industry Return		-0.504 ***			
		(0.079)			
Price$_{t-1}$			-0.133 ***	-0.167 ***	-0.270 ***
			(0.008)	(0.024)	(0.0067)
Adjusted R^2	0.37	0.37	0.24	0.22	0.106
Observations	176,527	176,169	175,598	175,244	175,244
Estimation	OLS	OLS	2SLS	2SLS	2SLS
Instrument	-	-	Stock	Industry	'Strong' Industry
Fixed Effects					
bond	Yes	Yes	Yes	Yes	Yes
year × month	Yes	Yes	Yes	Yes	Yes

This table reports the coefficients and standard errors from a regression of the Gamma measure of bond illiquidity on instrumental variables for bond prices. The instruments we use are: cumulative stock return (Columns 1 and 3); cumulative industry return (Columns 2 and 4); and 'strong' industry returns (Column 5). The regressions are estimated with either OLS (Columns 1 and 2) or 2SLS (Columns 3-5). All specification include bond and year-by-month fixed effects. Robust standard errors in parentheses are clustered by bond: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 16: Large Stock Price Decline Instruments: Summary Statistics

	Mean	Standard Deviation	25th Percentile	Median	75th Percentile	Observations
			Stock Return$_{t-1}$ ≤ 25th Percentile			
Stock Return$_{t-1}$	-0.099	0.076	-0.125	-0.080	-0.048	46,784
			Stock Return$_{t-1}$ > 25th Percentile			
Stock Return$_{t-1}$	0.046	0.087	-0.0003	0.031	0.072	131,853
			Stock Return$_{t-1}$ ≤ 10th Percentile			
Stock Return$_{t-1}$	-0.145	0.089	-0.180	-0.123	-0.086	20,086
			Stock Return$_{t-1}$ > 10th Percentile			
Stock Return$_{t-1}$	0.028	0.091	-0.021	0.018	0.063	158,551

This table reports summary statistics for lagged large monthly stock returns. The first two rows of the table report summary statistics for stock returns that are below or above the 25th percentile of monthly stock returns. The last two rows report summary statistics for stock returns that are below or above the 10th percentile of monthly stock returns.

Table 17: Instrumental Variables Regressions of the Effect of Large Stock Price Declines on Bond Illiquidity

	Gamma	Gamma	Gamma	Gamma
Price$_{t-1}$	-0.276 ***	-0.134 ***	-0.261 ***	-0.141 ***
	(0.011)	(0.023)	(0.011)	(0.022)
Adjusted R^2	0.06	0.24	0.09	0.23
Observations	175,302	175,302	175,302	175,302
Estimation	2SLS	2SLS	2SLS	2SLS
Instrument	Stock	Stock	Stock	Stock
	R$_{t-1}$ <p25	R$_{t-1}$ <p25	R$_{t-1}$ <p10	R$_{t-1}$ <p10
Fixed Effects				
bond	Yes	Yes	Yes	Yes
year	Yes	No	Yes	No
year × month	No	Yes	No	Yes

This table reports the coefficients and standard errors from a regression of the Gamma measure of bond illiquidity on instrumental variables for bond prices. The instruments we use are: large stock returns declines that are below the 25th percentile of the monthly stock return distribution (Columns 1 and 2) or below the 10th percentile of the monthly stock return distribution (Columns 3 and 4). The regressions are estimated using 2SLS and specification include bond and either year or year-by-month fixed effects. Robust standard errors in parentheses are clustered by bond: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 18: The Effect of Oil Price on the Illiquidity of Oil and Gas Bonds

	Gamma	Gamma	Amihud	Amihud	IRT	IRT
log(Oil Price$_t$)	-3.160 ***	-0.522	-0.014 ***	-0.005 ***	-0.004 ***	-0.001 ***
	(0.229)	(0.380)	(0.001)	(0.002)	(0.0002)	(0.0003)
Leverage$_{t-1}$		42.766 ***		0.145 ***		0.041 ***
		(5.315)		(0.020)		(0.004)
Leverage$_{t-1}$×log(Oil Price$_t$)		-8.836 ***		-0.028 ***		-0.008 ***
		(1.164)		(0.004)		(0.0008)
Adjusted R^2	0.292	0.327	0.240	0.251	0.284	0.303
Observations	18,359	17,636	27,134	25,966	29,452	28,120
Number of bonds	669	628	798	745	808	753
Fixed Effects						
bond	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes

This table reports the coefficients and standard errors from a regression of the three measures of bond illiquidity on log oil price, firm leverage, and an interaction between log oil price and leverage. The regressions are estimated for bonds issued by oil and gas companies. All specifications include bond and year-by-month fixed effects. Robust standard errors in parentheses are clustered by bond: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.